Managerial Sentiment, Investor Sentiment and Stock Returns

Ahmed Salhin

Submitted for the degree of

Doctor of Philosophy in Finance

Department of Accounting, Economics & Finance

School of Social Sciences

Heriot-Watt University

June 2017

Abstract

It is well established that investor sentiment plays a vital role in global financial markets. However, the sentiment of other economic agents has received less attention in the behavioural finance literature. This thesis aims to address the impact of managerial sentiment on the UK stock market. It investigates the performance of managerial sentiment in predicting stock returns relative to investor and consumer sentiments. In addition, it examines how sentiment is transmitted from managers to investors and whether the response of investor sentiment is asymmetric towards positive versus negative managerial sentiment. Finally, this thesis provides a comparative study of traditional and sentiment-augmented asset pricing models.

Using monthly data from January 1985 to December 2014 and a sample of consumer and business confidence indicators provided by the European Commission, the first chapter provides novel evidence on how managerial and consumer sentiment indicators affect stock returns. The findings show no support for consumer confidence as a predictor of stock returns. However, managerial sentiment shows a significant impact on aggregate market and sector return indices. Furthermore, results indicate that parameter estimates for sector groupings are not consistent, implying that the sentiment-return relationship differs across sectors and that parameters are sensitive to industry characteristics.

In the second chapter, the investigation extends to assess the long and short-run dynamics of the sentiment transmission from managers to investors. Using threshold autoregressive (TAR), momentum threshold autoregressive (MTAR), and asymmetric threshold vector error correction (ATVECM) models, the findings provide evidence on the impact of managerial sentiment on investor sentiment in support of the Catering Theory. Results show that investors' sentiments converge with long-run equilibrium relationships in response to positive rather than negative shocks in managerial sentiment. Furthermore, findings indicate that investor sentiment reacts negatively to positive managerial sentiment with a delay of four

months, suggesting an over-confidence in managers' expectations of their future business outcomes.

Finally, the third chapter examines the ability of managerial and investor sentiment to explain cross-sectional variation in stock returns. It compares the performance of CAPM, Fama & French (1993) Three factor model and Carhart (1997) four factor model to sentiment-augmented asset pricing models, which incorporate measures of both managerial and investor sentiment. The findings indicate that inclusion of sentiment factors significantly adds to the power of traditional asset pricing models to explain the cross-sectional variation in stock returns. In addition, results show that managerial sentiment outperforms investor sentiment in explaining three out of four test portfolios formed on size, book-to-market, volatility and size/momentum factors. Moreover, findings show that managerial sentiment exhibits stronger prediction power for size premium over short (1-3 months) forecasting horizon relative to investor sentiment. However, value premiums respond to changes in managerial and investor sentiment over the relatively longer time of 12 months. In addition, the investigation failed to find any significant relationship between sentiment indices and momentum premium.

This study has several implications for empirical researchers, practitioners and policy makers. It provides academics who are concerned with the empirical tests of asset pricing models with new insights on how the inclusion of managerial sentiment impacts the performance of longer term investigated models. For practitioners, our findings suggest that managerial sentiment and its impact on sector returns provide new opportunities for enhancing trading as well as asset allocation strategies. In developing investment strategies, practitioners may consider sectors that are more or less prone to sentiment in response to investor risk preferences. In addition, results on sentiment-augmented asset pricing models may be of interest to regulators who are concerned with the estimation of businesses' cost of capital when pricing public services.

Dedication

To my loving parents Fouad Salhin and Sediqa Mahmoud, without whom non of my success would be possible.

Acknowledgements

In the name of Allah, the Most Gracious and the Most Merciful

Alhamdulillah! All praise is due to Allah for giving me the strength and His blessings in completing my thesis. He supplied me with guidance, courage and patience to complete this research. Peace and blessing be upon my beloved prophet Muhammad, from whom I learned good manners and the love of knowledge.

Firstly, I pay sincere gratitude and profound appreciation to my supervisor Dr. Mohamed Sherif for the continuous support, patience, motivation, and immense knowledge during my PhD studies. He helped me throughout my research and the writing of my thesis. I thank him for his continuous encouragement and believing in my ability to succeed. I could not have imagined having a better supervisor and mentor for my PhD studies than Dr. Sherif. I am also deeply indebted to my second supervisor, Dr. Edward Jones, who provided me with insightful comments on my research and generous advices on my academic life. In addition to my supervisors, I would like to thank the School of Social Sciences (formerly the School of Management of Languages) for providing the funding towards this degree.

Most important of all, this journey would not have been possible without the support of my parents. Thank you for all the sacrifices you have made for me. You believed in me and wanted nothing but the best for me and my family. Your help was always infinite. I express my heart-felt gratitude to my parents in law Fatema Alzahraa and Salah Sabrah whose support and constant encouragement helped me through the hard times of this journey. I wish to thank my siblings; Amany and Fouad Elshafey, Radwa and Mohamed Samy, Saleh and Hadeer Salhin, Amr and Samir Sabrah for supporting me throughout writing this thesis and throughout my life. I am deeply grateful for your patience throughout my absence, especially when you needed me.

I also want dedicate this to my small family. Each and every one of you brings life and laughter into my heart. Ruqaya, Arwa and Adam, your happiness is my bliss. But most of all, I want my wife to know, that the success of this is due to her. Thoraia, you are the reason and purpose of my accomplishments. Saying that fills me with a lot of confidence and a lot of pride. When I look at you, I know I will always have the strength I need to get through anything. Despite the endless work of raising a family and countless sleepless nights, you remain beautiful, smart, and selfless. I am so grateful to be able to spend my life with you. My gratitude is never ending. Your sacrifices and patience made my studies possible, but it is our love that makes my life wonderful. You give me something to look forward to every day I wake up. You bring the best out in me. Thank you for every single thing you have done for me. I love you and always will.

I am greatly indebted to my closest friend Maysara Sayed whose friendship I deeply treasure. I have always received your support when needed. I wish to thank my fellow office mates Fisayo, Kenny, Sering, Wahida, and Yusuf for the stimulating discussions, encouragement, support and fun moments they have given me in the last four years. I will certainly miss your company in the future. I would also like to thank my family in the UK; Eltayeb Bensaad, Nazmi Sellami, Robert Short, Mossadek Yessaad and their families for their love and support during my stay in Edinburgh.

A paper extracted from the second chapter of this thesis titled 'Managerial Sentiment, Consumer Confidence and Sector Returns' (co-authored with Dr. Mohamed Sherif and Dr. Edward Jones) is published in the International Review of Financial Analysis. I would like to thank the editors and referees of this journal for their insightful comments on the study.

On a final note, I would like to thank the American Finance Association for the grant to attend their 2016 annual meeting in San Francisco. I would also like express my gratitude to Santander Bank for their mobility grant in which I used to support my research.

HERIOT WATT UNIVERSITY

ACADEMIC REGISTRY
Research Thesis Submission

Name:	Ahmed Salhin		
School:	School of Social Sciences		
Version: *(i.e. First, Resubmission, Final)*	Final	Degree Sought:	Doctor of Philosophy in Finance

Declaration

In accordance with the appropriate regulations I hereby-submit my thesis and I declare that:

1) the thesis embodies the results of my own work and has been composed by myself
2) where appropriate, I have made acknowledgement of the work of others and have made reference to work carried out in collaboration with other persons
3) the thesis is the correct version of the thesis for submission and is the same version as any electronic versions submitted*.
4) my thesis for the award referred to, deposited in the Heriot-Watt University Library, should be made available for loan or photocopying and be available via the Institutional Repository, subject to such conditions as the Librarian may require
5) I understand that as a student of the University I am required to abide by the Regulations of the University and to conform to its discipline.
6) I confirm that the thesis has been verified against plagiarism via an approved plagiarism detection application e.g. Turnitin.

* *Please note that it is the responsibility of the candidate to ensure that the correct version of the thesis is submitted.*

Signature of Candidate:		Date:	

Submission

Submitted By *(name in capitals)*:	
Signature of Individual Submitting:	
Date Submitted:	

For Completion in the Student Service Centre (SSC)

Received in the SSC by *(name in capitals)*:			
Method of Submission *(Handed in to SSC; posted through internal/external mail)*:			
E-thesis Submitted ***(mandatory for final theses)***			
Signature:		Date:	

Please note this form should be bound into the submitted thesis.
Academic Registry/Version (1) August 2016

Contents

List of Figures

List of Tables

Abbreviations

3FF	**T**hree **F**actor **M**odel
4FF	**F**our **F**actor **M**odel
ADF	**A**ugmented **D**ickey-**F**uller
AIC	**A**kaike **I**nformation **C**riterion
ATVECM	**A**symmetric **T**hreshold **V**ector **E**rror **C**orrection **M**odel
BTM	**B**ook **t**o **M**arket
CAPM	**C**apital **A**sset **P**ricing **M**odel
CCI	**C**onsumer **C**onfidence **I**ndicators
CEFD	**C**losed-**e**nd **F**und **D**iscount
CMSI	**C**ore **M**anagerial **S**entiment **I**ndex
EC	**E**uropean **C**ommission
ECT	**E**rror **C**orrection **T**erm
EMH	**E**fficient **M**arket **H**ypothesis
ESI	**E**conomic **S**entiment **I**ndicator
EW	**E**qually-**w**eighted
EXP	**E**xperian
GDP	**G**ross **D**omestic **P**roduct
GFC	**G**lobal **F**inancial **C**risis
HJ	**H**ansen and **J**agannathan
HML	**H**igh **M**inus **L**ow
ICB	**I**ndustry **C**lassification **B**enchmark
INF	**I**nflation
IPT	**I**ndex of **P**roduction (**T**otal)
ISENT	**I**nvestor **Sent**iment **I**ndex

KPSS	**K**wiatkowski-**P**hillips-**S**chmidt-**S**hin
LRE	**L**ong-**r**un **E**quilibrium
MOM	**Mom**entum
MSI	**M**anagerial **S**entiment **I**dex
MTAR	**M**omentum **T**hreshold **A**uto**r**egressive
NACE	**N**omenclature Statistique des **Ac**tivités **É**conomiques dans la Communauté Européenne
NAV	**N**et **A**sset **V**alue
NI	**N**ational **I**nstitutions
NIPOs	**N**umber of **I**nitial **P**ublic **O**fferings
ONS	**O**ffice of **N**ational **S**tatistics
PCA	**P**rincipal **C**omponent **A**nalysis
PP	**P**hilips-**P**erron
RI	**R**eturn **I**ndex
RMRF	**R**eturn on **M**arket portfolio minus **R**isk **F**ree rate
SD	**S**tandard **D**eviation
SDF	**S**tochastic **D**iscount **F**actors
SMB	**S**mall **M**inus **B**ig
TAR	**T**h**r**eshold **A**utoregressive
T-bill	**T**reasury **B**ill
UNEMP	**Unemp**loyment Rate
VARX	**V**ector **A**uto**r**egressive model with e**x**ogenous variables
VFTSEIX	**V**olatility of **FTSE**100 **I**nde**X**
VW	**V**alue-**w**eighted

List of Publications

Peer Reviewed Publications

- Shehata, N., **Salhin, A.**, and El-Helaly, M. (2017). Board Diversity and Firm Performance: Evidence from UK SMEs. *Applied Economics*, 1-16.
- **Salhin, A.**, Sherif, M. and Jones, E. (2016). Managerial Sentiment, Consumer Confidence and Sector Returns. *International Review of Financial Analysis*, 47, 24-38.
- **Salhin, A.** (2013). The impact of hard Discount Control Mechanism on the discount volatility of UK closed end funds. *Investment Management and Financial Innovation*, 10(3).

Working and Discussion Papers

- **Salhin, A.**, Sherif, M. and Jones, E. (2017). Sentiment Transmission between Managers and Investors.
- **Salhin, A.**, Sherif, M. and Jones, E. (2017). Managerial Sentiment, Asset Prices and Risk Premiums.
- **Salhin, A.**, Sherif, M. and Jones, E. (2016). Investor Sentiment and Sector Returns. *Centre for Finance and Investment Discussion Paper*, Heriot Watt University, (No. 1602).

Book Chapters Publications

- **Salhin, A.**, Kyiu, A., Taheri, B., Porter, C., Valantasis-Kanellos, N. and König, C. (2016). Quantitative Data Gathering Techniques. In: K. O'Gorman, R. MacIntosh and A. Paternson, *Research Methods for Accountancy and Finance*, 1st ed. Edinburgh: Goodfellow Publishers.

- Rae, S., **Salhin, A.**, Taheri, B., Porter, C., König, C., and Valantasis-Kanellos, N. (2016). Quantitative Data Analysis Approaches. In: K. O'Gorman, R. MacIntosh and A. Paternson, *Research Methods for Accountancy and Finance*, 1st ed. Edinburgh: Goodfellow Publishers.

Chapter 1

Introduction

"*Surely, an economy cannot be rational, which for its very being depends upon practices that are a disgrace to human nature.*"

– James Beattie, Dissertations Moral and Critical, (1783, p. 587)

1.1. Research background and motivation

In his early work on the behavioural foundations of economic theory, Kenneth Arrow (1986) argues that individual rationality is often an essential assumption for an economic theory to exist. The importance of the rationality assumption stems from its usefulness in providing solutions to frequent theoretical economic and financial problems in which economic agents are assumed to maximise their expected utility. For example, classical finance theory assumes investors are rational and diversify to optimize the statistical properties of their investments. In an economy with such rational investors, markets are efficient as asset prices fully reflect all available information and follow martingales (Lucas, 1978). Even if some investors are irrational and drive prices away from their intrinsic values, prices are brought back into equilibrium by the actions of arbitrageurs (Antoniou et al., 2013; Baker & Wurgler, 2006).

However, a considerable body of evidence has developed involving prolonged price anomalies in stock markets such as the closed-end fund puzzle, excess volatility, and calendar effects. Such anomalies cannot be understood under the traditional Efficient Market Hypothesis (EMH) of Fama (1970). In addition, studies show that arbitrage is limited and incurs costs that prevent rational investors from restoring market equilibrium (Shleifer & Vishny, 1997). Consequently, the influence of irrational investors or 'noise traders' on stock prices persist, so relaxing the rationality assumption becomes crucial to understand the dynamics of the stock market.

Moreover, psychological studies pioneered by Herbert Simon (1955, 1979) show that decision makers' rationality is bounded and individuals' reasoning processes frequently involve systematic errors. Furthermore, relaxing the rationality assumption led to developing theories that attempt to understand how investors make choices under risk and uncertainty. One example is the Prospect Theory developed by Kahneman & Tversky (1979). In Prospect Theory, investors evaluate their assets based on gains and losses instead of their final wealth. They are also loss averse in the sense that their avoidance of losses is greater than their attraction to gains. Moreover, individuals often rely on their intuition and feelings instead of on more deliberative, tedious reasoning (Glatzeder et al., 2010). Under such perspective, the dynamics of the economy and financial markets cannot be isolated from the nature of individual behaviour.

Therefore, the role of investor sentiment in causing mispricing of securities becomes more important than previously anticipated (Cook et al., 2003). However, researchers continue to debate investor sentiment measures and their impact on stock returns. For instance, closed-end fund discounts, which are considered to be a measure of (small) investor sentiment, remain a puzzle. Other sentiment measures like investor surveys, trading volume, mutual fund flow, retail investor trading, dividend premiums and insider trading have all been proposed as indicators of investor optimism and pessimism. Furthermore, several studies have used consumer confidence as a proxy for investor sentiment (Jansen & Nahuis, 2003; Lemmon & Portniaguina, 2006; Otoo, 1999).

However, the literature on behavioural finance has focussed less attention on the role of managerial sentiment in the stock market. Managers have superior information about their companies that gives them an advantage over investors. For example, Meulbroek (1992) shows that insider trading led to higher abnormal returns due to information asymmetry. We expect that if managers hold sentiment towards their businesses, it must be informed and have the capability to forecast future stock prices. Furthermore, and as evidenced by the literature, managers continuously aim to influence stock prices by using corporate activities to cater for investor sentiment (Baker & Wurgler, 2013). Revealing their sentiment towards the future of their businesses may represent one such activity. It follows then that investigating managerial sentiment would provide more insights into how managers interacts with investors in the stock market.

1.2. Study aims and contribution to knowledge

The objective of this thesis is to understand the impact of managerial sentiment on stock returns. To achieve our objective, we aim to answer three streams of questions; the first stream concerns the impact of managerial sentiment on stock returns at aggregate market and sector levels. In particular, the study attempts to answer the following questions: Does managerial sentiment significantly predict aggregate market returns? If so, is the aggregate sentiment-return relationship driven by specific sectors in the market? Does the impact of sentiment on stock returns differ across sectors? If so, what characteristics affect the nature of the relationship in each sector? What is the impact of major events on relationship between sentiment and returns? Does the impact differ in specific sectors more than others? How does managerial sentiment compare to consumer and investor sentiments in predicting stock market returns?

In the second stream, the main questions we attempt to answer are whether the sentiment of managers is transmitted to investor sentiment? If so, does investor sentiment asymmetrically respond to positive versus negative managerial sentiment? Finally, in the light of previous answers, the study aims to understand the impact of the inclusion of managerial and investor sentiment on the performance of traditional asset pricing models and what influence do managerial and investor sentiment indicators have on size, value and momentum anomalies.

The study contributes to the literature by answering these questions. It argues that managerial sentiment should be used as a powerful predictor of stock returns. It also sheds some light on the importance of studying sentiment at a disaggregated level since market participants do not hold the same sentiment towards each sector of the market. In addition, this thesis contributes knowledge on how managers interact with investors in the stock market and reveals some managerial practices that affect stock prices and how they drive investor sentiment to achieve their goals.

In chapter 2, the thesis investigates the relationship between managerial sentiment and sector returns. Using UK monthly data from January 1985 to December 2014 and a sample of consumer and business confidence indicators provided by the European Commission, we provide novel evidence on how managerial and consumer sentiment indicators affect stock returns. We find no support for consumer confidence as a predictor of stock returns. However, managerial sentiment shows a significant impact on aggregate market and sector return indices. Furthermore, we find that parameter estimates for sector groupings are not consistent, implying that the sentiment-return relationship differs across sectors. We also find parameters are sensitive to industry characteristics. Importantly, the overall sentiment-return relationship is dominated by sentiment associated with manufacturing firms.

In chapter 3, we investigate the relationship between managerial and investor sentiments in the UK market. As a starting point, we construct a core managerial sentiment index (CMSI) based on the findings of Salhin et al. (2016). Relative to individual measures of investor sentiment, our tests indicate that CMSI is a powerful predictor of stock returns and its performance is less sensitive to changes in stock market return indices. Moreover, we provide evidence for the impact of managerial sentiment on investor sentiment in support of the Catering Theory. In addition, we use Threshold Autoregressive (TAR), Momentum Threshold Autoregressive (MTAR), and Asymmetric Threshold Vector Error Correction (ATVECM) models to estimate the asymmetric long and short-run dynamics of sentiment transmission from managers to investors. Our findings show that investor sentiment converges to a long-run equilibrium relationship in response to positive rather than negative shocks in managerial sentiment. Furthermore, results indicate that investor sentiment reacts negatively to positive managerial sentiment with a delay of four months. These results suggest that managers are generally over-confident with regards to the future outcomes of their businesses.

The final chapter examines the ability of managerial and investor sentiment to explain UK stock returns. We compare the performance of CAPM, Fama & French (1993) Three Factor Model, and Carhart (1997) Four Factor Model to sentiment-augmented asset pricing models, which incorporate measures of both managerial and investor sentiment. Our findings indicate that the inclusion of sentiment factors significantly adds to the power of traditional asset pricing models in explaining the cross-sectional variation in stock returns. In addition, results show that managerial sentiment outperforms investor sentiment in explaining three out of four test portfolios formed on size, book-to-market, volatility and size/momentum factors. Furthermore, we evaluate the relative pricing errors of the models using the non-parametric distance of Hansen & Jagannathan (1997). Our results offer evidence that managerial sentiment models yield small distance errors relative to traditional asset pricing models. Moreover, we investigate whether managerial and investor sentiment can predict size, value, and momentum premiums over different forecasting horizons. We show that managerial and investor sentiment indicators exhibit stronger forecasting power for size premiums over a shorter forecasting horizon. On the contrary, value premiums are affected by managerial and investor sentiment over a longer horizon of 12 months. However, we find no evidence for the impact of sentiment indices on momentum premium.

1.3. The UK stock market

The focus of this study is on the UK market. The main reason for selecting the UK market is due to the availability of data on managerial sentiment for the aggregate market and for sectors. Data for our sample is provided by the European Commission (EC) which spans the period from January 1985 to December 2014. The data provides essential information for business activities and short-term forecasting and is often used to predict turning points in the economic cycle.

In addition, the London Stock Exchange is considered one of the major stock exchanges in the world and is the largest in Europe. It has roots that stretchs back to the coffee houses of the 17th century and it operates in London which ranks at the top of the Global Financial Centres Index (see Figure 1.1). The exchange has approximately 3000 companies from over 70 countries that are listed and traded on its markets. Therefore, investigating the UK market would provide more insights for understanding the impact of managerial sentiment in Europe and the global market.

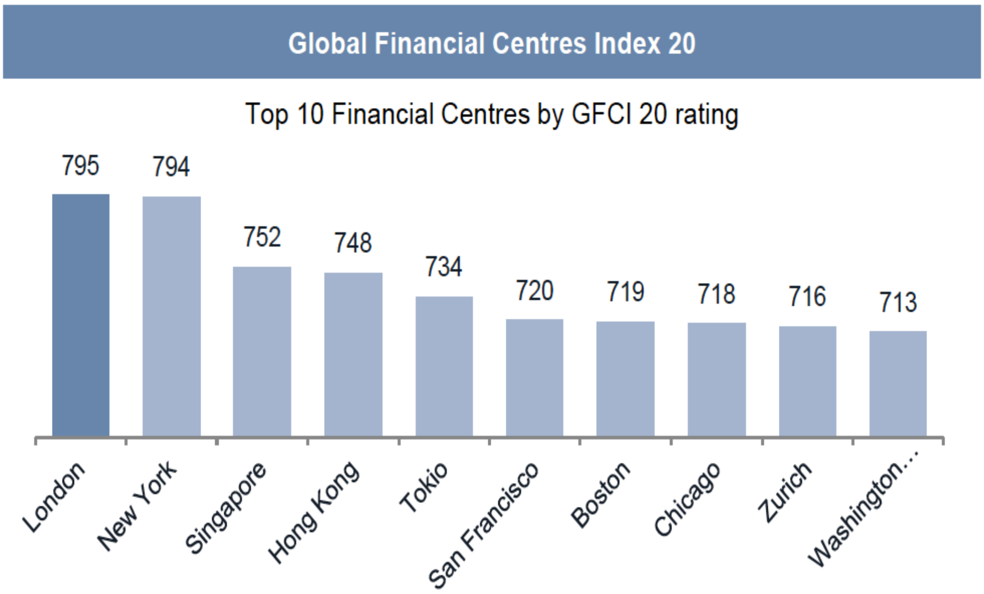

Figure 1.1: Global Financial Centres Index

The figure is adapted from Accessing the Global Market Through London report, available at: http://www.lseg.com

Furthermore, another reason for investigating the UK market is to anticipate future research opportunities. The European Commission (EC) provides the data on managerial and consumer sentiments for 27 European Countries. For every country, businesses and consumers are surveyed for their opinions regarding economic and business conditions. The surveys are then harmonized to generate comparable data for the countries that have been surveyed. The availability of such data will allow for an expansion of this research to other European countries.

1.4. Outline of the thesis

The rest of the thesis is structured as follows: Chapter 2 investigates the relationship between managerial sentiment and stock returns at the aggregate market and sectors levels. Chapter 3 examines sentiment transmission from managers to investors. The empirical tests of traditional versus sentiment-augmented asset pricing models are detailed in chapter 4. Chapter 5 concludes the thesis.

Chapter 2

Managerial Sentiment, Consumer Confidence and Sector Returns

2.1. Introduction

Studies in the relatively recent field of behavioural finance have identified pricing anomalies which contradict the expectations of the efficient markets hypothesis. In particular, considerable attention has focused on how market prices are influenced by investor sentiment (Baker & Wurgler, 2006; Baker et al., 2012; Da et al., 2015; Lee et al., 1991). Investor or market sentiment is defined in the financial literature as the prevailing attitude or feeling in the market as revealed by movements of stock prices. A large and growing literature examines the relationship between various proxies for investor sentiment and stock returns. We add to this literature in two ways. Using UK data from European Commission (EC) business and consumer surveys between January 1985 and December 2014, we analyse managerial sentiment as a proxy for investor sentiment. Further, we examine the impact of managerial sentiment and consumer confidence, a commonly used proxy for investor sentiment, on stock returns at the sectoral level.

Investment-related sentiment is not directly observable and so previous studies have used a number of proxies - including investor surveys, closed-end fund discounts, mutual fund flows and composite sentiment indices - which have been found to significantly influence stock prices (Baker & Wurgler, 2006; Frazzini & Lamont, 2008; Lee et al., 1991). In addition, various studies use information provided by consumer sentiment surveys as measure of investor sentiment (Ferrer et al., 2016; Fisher & Statman, 2003; Jansen & Nahuis, 2003; Otoo, 1999). However, their findings do not provide a consistent view of the association between consumer confidence and market values.

Contrary to consumer confidence studies, surveys of business confidence assess managerial sentiment regarding past and future performance. When compared to consumers, managerial access to business information allows for a more informed opinion of future market conditions. In this view, managerial sentiment informs investor sentiment and thereby stock-pricing. Baker & Wurgler (2013) include both sentiment from corporate insiders and surveys of consumer confidence in their list of potential proxies for investor sentiment. Thus, the first contribution of our study is to provide evidence on how managerial sentiment differs from consumer confidence in predicting stock returns.

Furthermore, sentiment studies predominantly examine the impact of investor sentiment proxies on aggregate market sentiment. Brown & Cliff (2004) suggest that aggregate sentiment measures are used primarily due to data limitations since sentiment measures such as surveys, advance-decline ratio and closed-end fund discounts are not commonly available at disaggregated levels. In addition, Brown and Cliff argue that aggregate sentiment effects become negligible when the number of stocks affected by high sentiment equals the number of stocks affected by low sentiment. This argument suggests that, when sentiment varies between sectors, aggregate measures of sentiment may not be sufficient to detect impacts on stock prices. Thus, our study also provides new evidence on the impact of investor sentiment on sector returns. Moreover, increasing attention to industry effects in the investment allocation literature provides further support for examination of sentiment at industry level. For example, Chen et al. (2006) suggest that industry-based investment strategies are more effective than country based strategies. Marcelo et al. (2013) find that diversification based on industry leads to more efficient portfolios.

By examining the associations between managerial sentiment and sector returns, we provide significant evidence for investors and portfolio managers regarding which industries are most susceptible to sentiment. In addition, our findings are informative for policy-makers and regulators whose decisions affect stock prices. The rest of this chapter is structured as follows: The next section reviews the existing literature. Section 3 describes the data and provides some descriptive statistics and preliminary tests. Section 4 describes the methodology used and discusses results. Section 5 concludes.

2.2. Literature review

There has been a long running debate in the academic literature regarding the success of the efficient market hypothesis in explaining the predictability in asset returns. The classical theory assumes financial markets are efficient; investors are rational and diversify to optimize the statistical properties of their investments. Even if some investors are irrational, prices are brought back into equilibrium by the actions of arbitrageurs (Antoniou et al., 2013; Baker & Wurgler, 2006). It follows then that there is no role for investor irrationality on asset pricing. However, research on behavioural finance confirms that investor sentiment affects stock prices and mispricing is persistent due to costly and non-profitable arbitrage (Lee et al., 1991).

2.2.1 Market-based measures of sentiment

Although the relation between investor sentiment and stock returns is well documented in numerous studies (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004; Da et al., 2015; Schmeling, 2009), researchers continue to debate sentiment measures and their impact on stock returns. Indeed, there is a large literature that documents the measurability of investor sentiment and its impact on stock prices. Despite using different proxies to measure sentiment, the overall conclusion is that sentiment is highly correlated with stock returns. For example, Baker & Wurgler (2006) use a group of sentiment proxies and principal component analysis to investigate the relationship between sentiment and stock returns. Their results suggest a significant correlation between sentiment and lead returns, in particular younger and smaller stocks. Such stocks are more likely to attract the attention of optimists and speculators who buy on the hype of stocks and sell after the hype is over. Similarly, using technical indicators, survey data from investor intelligence, and trading activity-related variables, Brown & Cliff (2004) find evidence supporting the co-movement of sentiment measures with market returns, particular in the long-run.

Another strand of research focuses on the predictability of sentiment to stock returns using individual sentiment proxies. For example, Fisher & Statman (2000) used Wall Street strategists' mean allocation to stocks as a proxy for sentiment of large investors and report a negative relationship with S&P 500 returns. In another key study, Lee et al. (1991) used closed-end fund discount as a proxy for investor sentiment, and argued that closed-end fund discounts and small stocks owned by individuals co-move with investor sentiment. In the same vein, Kaniel et al. (2008) use the imbalances in the orders of individual stocks on the NYSE as a sentiment measure and find evidence supporting strong predicative power of future returns. Further, using net flows of mutual funds as a proxy of investor sentiment, Ben-Rephael et al. (2012) found a contemporaneous relationship between net exchanges to equity funds and changes in stock market prices. Similarly, issuing higher levels of equity shares compared to debt is believed to capture the market enthusiasm and predicts subsequent lower returns (Baker & Wurgler, 2000). Lee et al. (1991) use the number of IPOs and average first day returns of IPOs as proxies for investor sentiment. They find that companies tend to time the market and issue IPOs during periods of positive sentiment. Consistent with Lee et al. (1991), Cornelli et al. (2006) indicate that investor sentiment can explain the underperformance of the IPOs returns.

2.2.2 Survey-based measures of sentiment

Due to the lack of directly-observable indicators measuring investor sentiment, a number of previous empirical studies employ consumer confidence indices to proxy for investor sentiment (Schmeling, 2009). Consumer confidence indicators (CCIs) are perceived to contain information that predicts future market conditions such as household spending, total personal consumption growth and expenditures on consumer durables (Bram & Ludvigson, 1998; Carroll et al., 1994; Throop, 1992). Furthermore, stock market studies report a contemporaneous correlation between CCIs and stock market returns. However, results vary on the direction of causality between them. For example, Fisher & Statman (2003) investigate the validity of consumer confidence as a proxy of the individual investor sentiment and its predictive power of stock returns. Overall, they find a positive contemporaneous relationship between changes in consumer confidence and S&P 500 returns. In another study, Otoo (1999) use US data and find that consumer confidence is affected by the increase in equity value. Elsewhere, using EU data, Jansen & Nahuis (2003) find evidence supporting the relationship between CCIs and stock returns, in particular in the short run. Additionally, they reported that stock returns predict consumer confidence but not vice versa. In contrast, Schmeling (2009) found that consumer confidence negatively predicts stock market return for 18 industrialized countries. Further, Charoenrook (2005) investigate the University of Michigan Consumer Sentiment Index explanatory power for stock market return and find a positive relationship between the changes in consumer sentiment and the contemporaneous excess market returns in the long run, but negatively related to the future excess returns at one-month and one-year horizons.

Consistent with Brown & Cliff (2004), Wang et al. (2006) and Canbaş & Kandır (2009) indicate that investor sentiment proxies are caused by stock returns and volatility rather than vice versa. According to Ferrer et al. (2016), the causality from stock returns to CCIs could be interpreted as an information effect (higher stock returns means good economic conditions and higher optimism) or as a wealth effect (higher value of equity leads to higher wealth). On the other hand, Lemmon & Portniaguina (2006) identified the forecasting power of investor sentiment, as measured by consumer confidence, in predicting stock market returns and find a relationship between consumer confidence and stock returns only for small stocks and stocks with low degrees of institutional ownership. Similarly, Schmeling (2009) suggests that there is a two-way causality such that investor sentiment depends on previous returns and the returns depend on previous investor sentiment. For trading strategies, Antoniou et al. (2013) find that CCIs affects the profitability of momentum-based strategies but only in periods of high optimism. They argue that in periods of high sentiment, smaller investors are reluctant to sell losing stocks. Conversely, larger investors are usually ready to sell losing stocks promptly and profit from momentum strategies.

Most recently, Ferrer et al. (2016) argue for the inappropriateness of consumer confidence indicator as a proxy for investor sentiment. Using data for the EU and the US, they investigated the relationship between stock returns and CCIs around the dotcom bubble period. Their finding suggests that CCIs failed to forecast stock returns, particularly for the EU countries after the dotcom bubble. Importantly, the majority of studies finding support for CCIs as a measure of sentiment have used US data. This may reflect the sentiment of individual investors who represent a larger proportion of US market participants compared to the EU market.

2.2.3 Sector effect

The majority of literature on the relationship between investor sentiment and stock returns concerns the aggregate market. Notably, studies on how equity managers allocate their investment pay considerably more attention to sectoral effects on returns and diversification strategies (Baca et al., 2000; Cavaglia et al., 2000; Griffin & Karolyi, 1998). For example, Chen et al. (2006) investigated the importance of sector effects in diversification strategies for developed and emerging markets. Their findings suggest that, for developing markets, sector-based strategies become more important than country-based strategies. For emerging markets, they advocate sector-based strategies despite finding that country-based strategies still dominate the allocation of investments in these markets.

Another stream of research provides evidence on the significance of industry factors on periods with high volatility (see for example, Marcelo et al., 2013; Soriano & Climent, 2006). In a key study, Marcelo et al. (2013) find that industry-based diversification leads to more efficient portfolios. Additionally, they provide an evidence supporting diversification across industries provides better protection in periods of high volatility compared to diversification associated with countries. In addition to the impact of industries on investment diversification, recent studies have investigated industry-level returns as predictors of economic activity. Laopodis (2016) examines the relationship between industries returns, macroeconomic variables and aggregate market returns. The findings show that industry portfolios explain macroeconomic indicators such as inflation, unemployment rate and dividend yield. Further, Laopodis demonstrates that returns in some industries such as Food, Mining, Consumer, Construction and Machinery contain valuable information supporting decisions related to investments on the stock market. Overall, findings with respect to the importance of industry effect provide support for our investigation of the relationship between sentiment and return at a sectoral level.

As evidence against the reliability of consumer confidence indicator has accumulated and the importance of investigating the sentiment-sector return relationship have been documented, in our study, we argue that managerial sentiment is an appropriate predictor of stock market return since managers possess direct information of the past, current and the future of their businesses compared to consumer. In addition, the availability of data on sector-specific sentiment provides the ability to asses how the sentiment-return relationship is shaped by the characteristics of each industry.

2.3. Data and descriptive statistics

2.3.1 Data on investor sentiment

This study uses confidence indicators published by the European Commission (EC) as proxies for investor sentiment. The indicators are calculated using business and consumer surveys which are conducted on a monthly basis by national institutions (such as ministries, statistical offices, central banks, research institutes, business associations or private companies) in 27 European countries. For every country, businesses and consumers are surveyed seeking their opinions regarding the economic conditions and short term forecasting. The surveys are then harmonized to generate comparable data for the countries that have been surveyed.

For business indicators, five surveys are conducted on a monthly basis with more questions added to every survey on a quarterly basis. The surveys cover Manufacturing, Construction, Retail Trade, Services, and Financial Services sector groupings. A biannually investment survey of the Manufacturing sector is conducted to gather information on companies' investment plans. Classification of business surveys into sectors follows the classification of economic activities in the European Community (NACE Rev. 2). The EC includes multiple industries in each of the five sector groupings. Therefore, each survey under the NACE Rev. 2 classification reflects one or more industries of the Industry Classification Benchmark (ICB). For example, the EC Manufacturing sector cover Industrials and Basic Materials industries from the ICB.[1]

Survey data is collected for the period from January 1985 to December 2014 for all sectors except the services sector. For the Services sector, data is not available until January 1997. Prior to May 2006, the Services sector surveys included Financial Services firms. From May 2006 onwards, Financial Services sentiment was surveyed separately. This indicates a statistical break in the Services

[1] More information is available in the Joint Harmonised EU Programme of Business and Consumer Surveys guide available at http://ec.europa.eu, accessed on 26 May 2016.

sector sample. Therefore, we take the Services sector sentiment as our indicator for the sample period from May 2006 to December 2014. For Financial Services, confidence indicators is not available for individual countries but rather for the whole EU. Hence, they are excluded from our analysis as a sentiment index. The number of companies covered by EC surveys by sector is displayed in Table 2.1.

Table 2.1
Sample size for business surveys in the UK and the EU.

This table presents the sample size for business surveys in the UK and the EU. In the UK, business surveys are collected by National Institutions (NI) such as the Confederation of British Industry (CBI) and Experian (EXP).

Sectors	Manufacturing	Services	Retail trade	Construction
UK	1500	1000	500	750
EU	38,270	43,720	30,730	22,140
NI	CBI	CBI	CBI	EXP.

Monthly surveys are performed in the first ten days of each month for all business and consumer indicators. Survey questions use a Likert-type scale with responses divided into three, five or six options in an ordinal scale. Example of replies are (“increase”, “remain unchanged”, “decrease”), (“more than sufficient”, “sufficient”, “not sufficient”), or (“too large”, “adequate”, “too small”). Sample questions for each sector and the method of constructing confidence indicators are included in Appendices 1 and 2.[2]

The aggregate sentiment indicator for the market, Economic Sentiment Indicator (ESI), is the weighted average of all confidence indicators with 40% to Manufacturing, 30% to Services, 20% Consumers, 5% for each of Construction and Retail Trade sectors.[3] The descriptive statistics for ESI and sector confidence indicators are shown in Table 2.2.

Values for ESI are transformed to have a mean of 100 and standard deviation of 10. The whole market is identified as optimistic about the economy if the value of the ESI is above 100 and pessimistic if it is below 100. Each of the business and consumer confidence indicators has a mean equals zero. Values of confidence indicators along with Economic Sentiment Indicator are presented in Figure 2.1.

[2] More information on the method is available on the EC web site at: http://ec.europa.eu, accessed on 26 May 2016.
[3] Economic Sentiment Indicator is the term issued by the EC to describe their indicator.

Table 2.2
Descriptive statistics and correlation for economic, consumer and managerial sentiment indicators.

Data covers the period from January 1985 to December 2014 for the economic sentiment, consumer confidence and sector sentiment indicators except Services sector. Services sector sample starts from May 2006 to December 2014. The fourth column represents the "trimmed" values at 1%.

Panel A : Descriptive statistics

Economic and Consumer Confidence Indicators

	mean	sd	trimmed	min	max
Economic	101.77	10.71	101.86	64.60	127.20
Consumer	-9.29	8.64	-9.23	-35.20	7.60
Managerial sentiment					
Manufacturing	-7.33	12.59	-7.23	-49.00	21.60
Construction	-17.19	23.40	-17.17	-79.30	43.10
Retail Trade	3.38	13.78	3.58	-47.10	29.00
Services	-4.96	20.8	-4.79	-57.40	30.40

Panel B: Correlations

	Manufacturing	Construction	Retail Trade	Services
Construction	0.60***			
Retail Trade	0.66***	0.55***		
Services	0.81***	0.86***	0.75***	
Consumer	0.43***	0.63***	0.52***	0.84***

Levels of significance for correlation coefficients are ***:0.01, **:0.05, *:0.1.

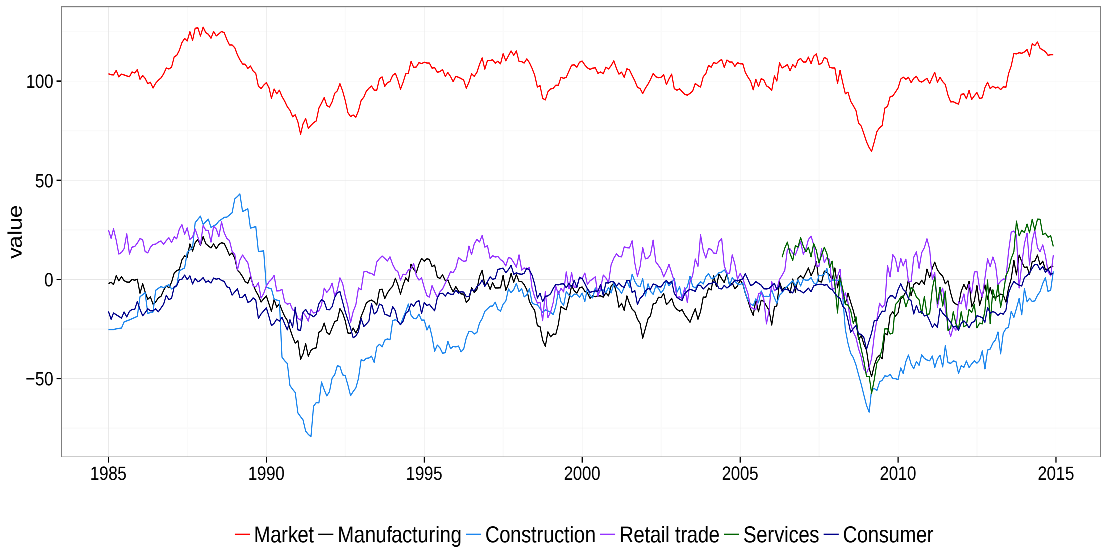

Figure 2.1: Sentiment indicators

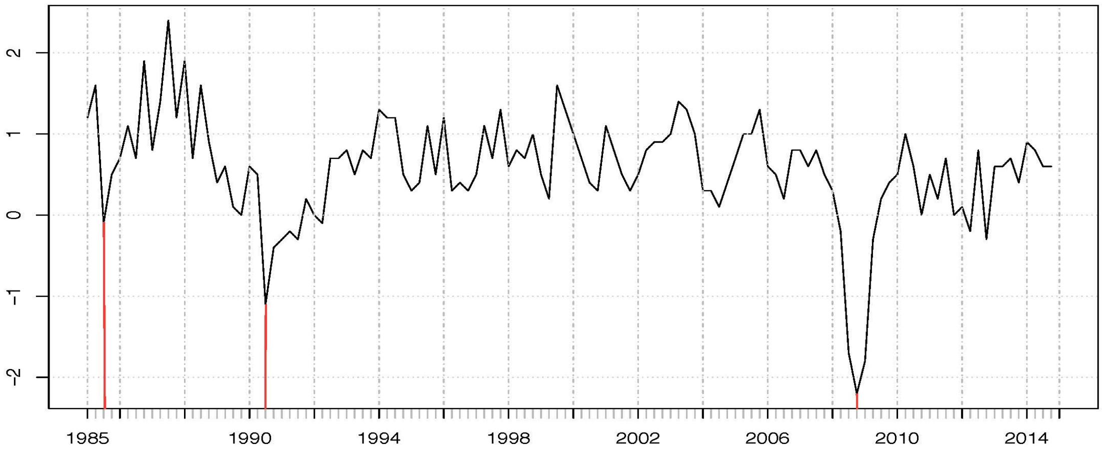

Figure 2.2: UK GDP growth rate

The red line corresponds to major events which affected the UK economy (recessions of the late-1980s, early-1990s and the Global Financial Crisis (GFC), respectively)

All confidence indicators reflect major events in the economy. Figure 2.2 shows the growth rate of UK GDP and indicates the major events affecting confidence indicators during the period. Confidence indicators are associated with the major events that have affected the UK economy including the recession of the late-1980s, recovery in the mid-1990s and the Global Financial Crisis (GFC) can clearly be seen from the graph in Figure 2.1. On average, Retail Trade and Services sectors encounter high average levels of confidence indicators. Notably, the Construction industry is associated with a lower level of sentiment. Importantly, sentiment in the Construction industry is highly sensitive to shocks in the market. Furthermore, the effect of these shocks on the Construction sector sentiment takes more time to return to mean levels compared to other sectors. Confidence indicators are more volatile for Construction, Retail Trade and Services compared to Manufacturing and Consumer confidence indicators.

Correlations between confidence indicators are relatively high and significant between sectors. However, plotting correlations with 12 month windows over the sample period shows a wave-like pattern indicating unstable correlation (see Figure 2.3). Confidence indicators have strong positive correlation following major events. When the market experiences stability, correlation reverts to mean levels.

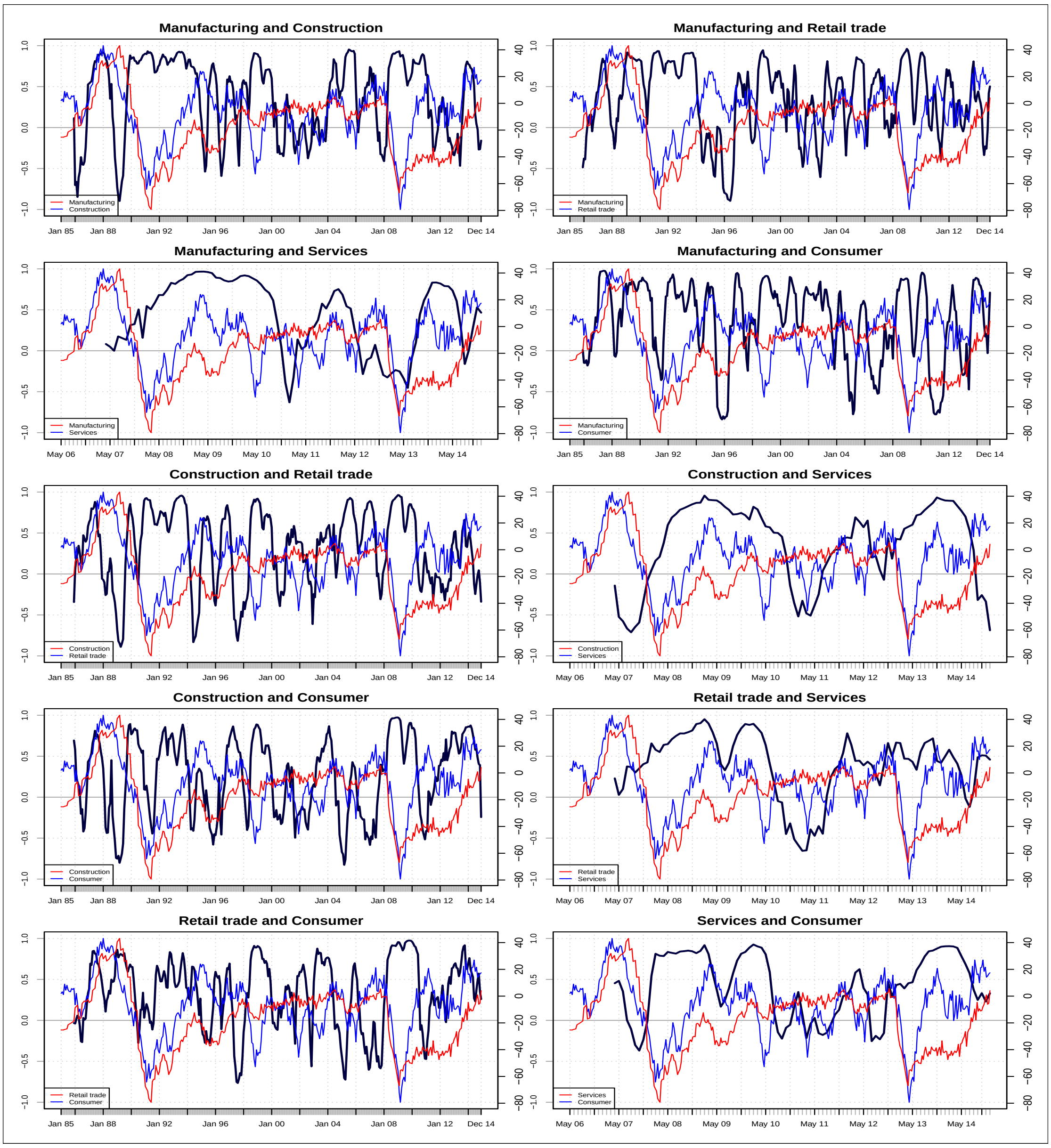

Figure 2.3: Rolling correlation between sentiment indicators

Each graph plots the rolling correlation between two sentiment indicators using 12 month window.

2.3.2 Data on stock returns

Our analysis covers the relationship between consumer and managerial sentiment and stock returns for the aggregate market and individual sectors. We used FTSE All Share Index monthly returns for the aggregate level of stock returns. Following Jansen & Nahuis (2003), we calculated monthly returns as the simple average of the first ten days returns to avoid any spurious causality due to non-synchronous observations.

Sector returns have been obtained by classifying FTSE All-Share Index constituents into sectors. For each firm, we used the Industry Classification Benchmark (ICB) obtained from Datastream. Sector returns are matched to the 'Classification' of economic activities in the European Community (NACE Rev. 2). For example, using the ICB system, Associated British Foods plc is classified under the "Food Producer" sector name. Consequently, the company has been placed under the "Manufacture of food products" category in the NACE. This ended up with four sector return indices that match the corresponding sector sentiment indicators and another index for Financial Services sector.[4] The number of firms in each sector is as follows: Manufacturing (212); Construction (13); Retail Trade (34); Services (78); and Financial Services (278).

Sector returns, as displayed in Figure 2.4, are the summation of daily returns weighted by the market value of its constituents. Returns are winsorized at 1% level to eliminate the effect of outliers. Both FTSE All-Share Index and sectors prices data are obtained from Datastream for the period from January 1985 to December 2014. Table 2.3 shows descriptive statistics and correlation coefficients for market and sector returns.

[4] The reason for the inclusion of Financial Services return index despite the unavailability of a corresponding sentiment index is its importance in the stock market. The sector accounts for 24.07% and 20.34% of the FTSE All-Share and FTSE 100 indices constituents, respectively.

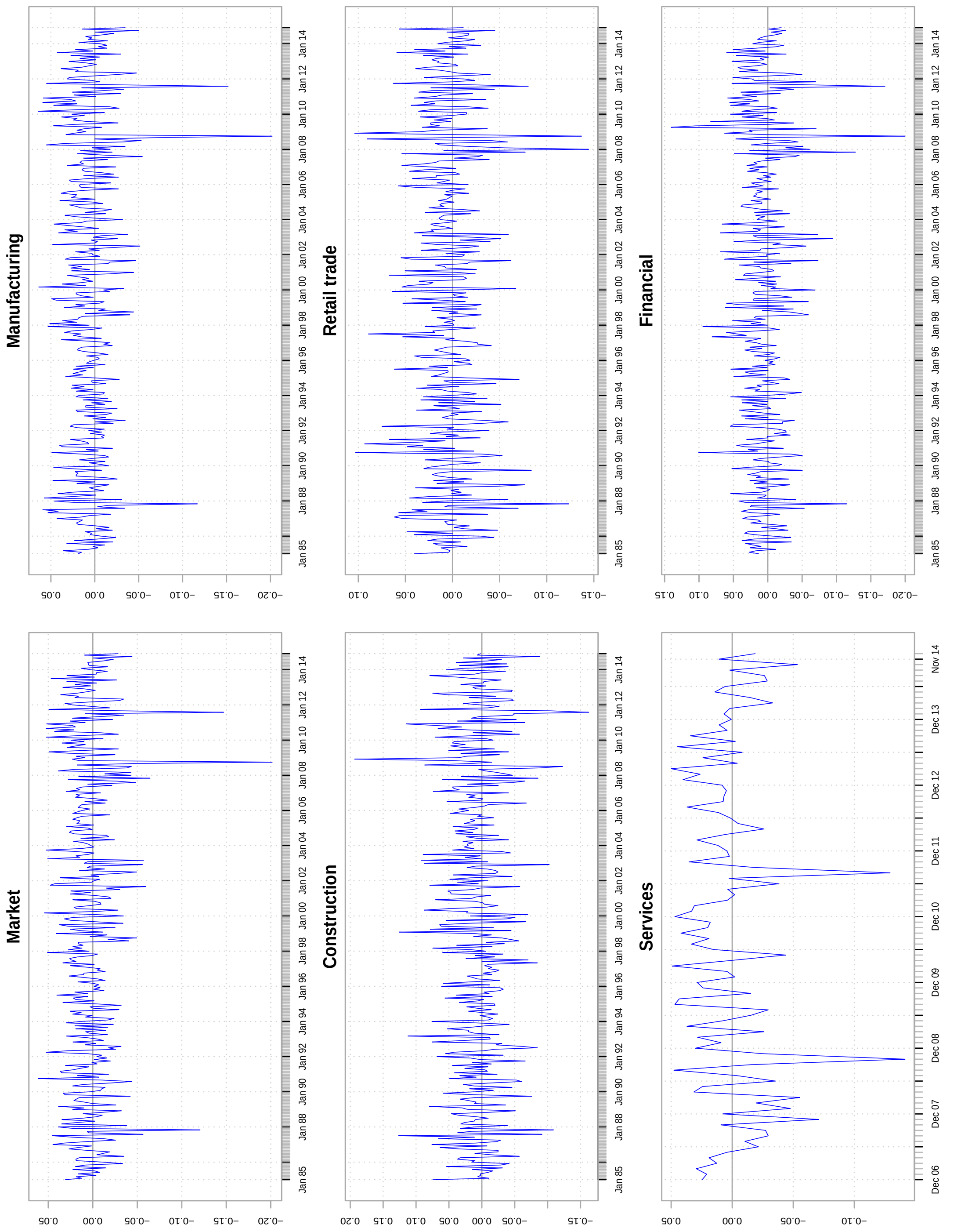

Figure 2.4: Market and sectors returns

Table 2.3
Descriptive statistics and correlation for market and sector returns.

Data covers the period from January 1985 to December 2014 for the whole UK market and sectors returns except Services sector. Services sector sample starts from May 2006 to December 2014. To remove the impact of any outliers, we "trimmed" our data at 1% level.

Panel A: Descriptive statistics

	mean	sd	trimmed	min	max
Market	0.34%	2.76%	0.43%	-20.17%	6.13%
Manufacturing	0.58%	2.77%	0.67%	-20.22%	6.44%
Construction	0.56%	4.27%	0.55%	-16.25%	19.32%
Retail trade	0.36%	3.29%	0.40%	-14.46%	10.39%
Services	0.23%	3.19%	0.32%	-14.02%	5.12%
Financials	0.65%	3.54%	0.70%	-19.99%	14.06%

Panel B: Correlations

	Market	Manufacturing	Construction	Retail	Services
Manufacturing	0.89***				
Construction	0.54***	0.51***			
Retail Trade	0.73***	0.62***	0.50***		
Services	0.89***	0.80***	0.58***	0.77***	
Financials	0.88***	0.71***	0.50***	0.67***	0.83***

Levels of significance for correlation coefficients are ***:0.01, **:0.05, *:0.1.

2.3.3 Preliminary tests

Plotting the autocorrelation function for all time series shows large autocorrelations in confidence indicators.[5] That in turn leads us to examine whether our time series are unit-root non-stationary using Augmented Dickey-Fuller (ADF), Philips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Table 2.4 summarizes all tests for both level and differenced data. Based on the three tests, all time series except Services sectors are stationary on their level values (i.e. they have *I(0)*).

Notably, both ADF and PP tests confirms that Services series is nonstationary and has a unit root. On the other hand, KPSS test for stationarity shows that the series is stationary. Differencing the series removes the nonstationarity behaviour and all tests produce the same results. Consequently, service sector has either *I(1)* based on ADF and PP tests or *I(0)* based on KPSS test. The different behaviour of the Services sector CI will lead us to change the model used to test its relationship with different returns series. This will be discussed in details in the next section.

[5] Appendix 3 reports the graphs for autocorrelation functions for level and differenced series.

Table 2.4
Unit root tests.

Tests are based on 360 observations for all variables except Services sector which has 104 observations. Models used for unit root test specified to include the intercept with lags of the variable. Lag length for Augmanted Dicky-Fuller (ADF) tests are determined by Akaike Information Criterion with maximum of twelve lags differences. Newey-West procedure is used to calculate bandwidths for both Philips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. For spectral estimation, Bartlett's kernel is used.

	Level			Differenced		
	ADF	*PP*	*KPSS*	ADF	*PP*	*KPSS*
Confidence Indicators						
Market	-4.13	−2.95	0.10	-8.37	−20.15	0.05
(p-value)	(0.000)	(0.018)		(0.000)	(0.000)	
Manufacturing	-4.22	−3.26	0.10	-6.04	−22.75	0.04
(p-value)	(0.000)	(0.006)		(0.000)	(0.000)	
Construction	-3.44	−1.96	0.17	-5.04	−20.30	0.10
(p-value)	(0.009)	(0.176)		(0.000)	(0.000)	
Retail Trade	-4.61	−4.24	0.24	-9.08	−21.80	0.03
(p-value)	(0.000)	(0.000)		(0.000)	(0.000)	
Services	-1.28	−1.59	0.20	−3.78	−13.62	0.14
(p-value)	(0.228)	(0.114)		(0.000)	(0.000)	
Consumer	-2.78	−3.09	0.17	-13.43	−21.28	0.03
(p-value)	(0.050)	(0.024)		(0.000)	(0.000)	
Stock Returns						
Market	-10.00	−18.52	0.06	-10.22	−48.14	0.00
(p-value)	(0.000)	(0.000)		(0.000)	(0.001)	
Manufacturing	-12.63	−17.66	0.13	-9.25	−46.40	0.00
(p-value)	(0.000)	(0.000)		(0.000)	(0.001)	
Construction	-12.73	−20.06	0.06	-9.32	−54.19	0.00
(p-value)	(0.000)	(0.000)		(0.000)	(0.001)	
Retail Trade	-7.17	−19.65	0.02	-9.80	−51.53	0.00
(p-value)	(0.000)	(0.000)		(0.000)	(0.001)	
Services	-3.35	−8.73	0.10	-10.52	−21.06	0.01
(p-value)	(0.000)	(0.000)		(0.000)	(0.000)	
Financials	-6.74	−19.60	0.03	-10.17	−50.91	0.00
(p-value)	(0.000)	(0.000)		(0.000)	(0.000)	

2.4. Methodology and findings

We use Granger-Causality test to examine the causality between managerial sentiment and stock returns (Granger, 1988). For the causality from sentiment to return, the test determines whether lagged values of sentiment contain information that is not already included in past values of stock returns, and vice versa. Our choice of the methodology is consistent with previous studies on consumer confidence as a proxy for investor sentiment (Ferrer et al., 2016; Fisher & Statman, 2003; Jansen & Nahuis, 2003; Otoo, 1999; Schmeling, 2009). Some studies which use similar methods but different measures of sentiment to examine the sentiment-returns relationship include Brown & Cliff (2004), Chung et al. (2012), Kumar & Lee (2006), Wang et al. (2006). We conduct Granger-Causality tests on the base of the following equations:[6]

$$R_t = \alpha_r + \sum_{i=1}^{k} \beta_{ri} R_{t-i} + \sum_{i=1}^{k} \gamma_{ri} S_{t-i} + \upsilon_{rt} \tag{2.1}$$

$$S_t = \alpha_s + \sum_{i=1}^{k} \beta_{si} S_{t-i} + \sum_{i=1}^{k} \gamma_{si} R_{t-i} + \upsilon_{st} \tag{2.2}$$

where S_t denotes sentiment indicator at time t; R_t is the monthly return of sector groupings and the economy at time t; υ is a disturbance term; and k is the maximal lag.

For Services sector sentiment, we employ equations 2.1 and 2.2 using level values with maximal lag to k. In addition, when ADF and PP tests are correct that the Services sentiment series is $I(1)$, we use equation 2.3 and 2.4 and follow the procedures suggested by Toda and Yamamoto (1995) to fix the asymptotics of the test.

$$R_t = \alpha_r + \sum_{i=1}^{k+I} \beta_{ri} R_{t-i} + \sum_{i=1}^{k+I} \gamma_{ri} S_{t-i} + \upsilon_{rt} \tag{2.3}$$

$$S_t = \alpha_s + \sum_{i=1}^{k+I} \beta_{si} S_{t-i} + \sum_{i=1}^{k+I} \gamma_{si} R_{t-i} + \upsilon_{st} \tag{2.4}$$

where I is the maximal order of integration in the model which in our study equals 1. The lag is only used to estimate the coefficients but not in use when estimating Wald test to test whether β_i and γ_i are jointly zero.

[6] Since unit root and stationarity tests result in a stationary *I(0)* series for most of the sectors, VAR models specification uses both sentiment and returns series at their level.

Equations 2.1 and 2.3 indicate that sentiment is believed to Granger-cause stock prices when lagged sentiment contain information that is not already included in past values of stock returns. The null hypothesis for estimated models is H_0: Sentiment does not Granger-cause returns. Equations 2.2 and 2.4 are used to test the relationship from returns to sentiment. Table 2.5 reports Granger-causality test results in both directions. The cross-correlation functions between indices and returns are displayed in Appendix 4.

Where the right hand side of each cross correlation plot represents the correlations between returns at time t and sentiment at time $t + k$ (i.e. returns leads sentiment), the other side reveals the correlations between returns at time t and lags of sentiment. The pattern of the plots illustrates that sentiment is positively correlated to lags of returns. Furthermore, this correlation disappears with the long lags. In contrast, returns are negatively correlated to lags of sentiment suggesting that high returns are associated with low sentiment in previous periods and vice versa, which is consistent with Brown & Cliff (2005), Baker & Wurgler (2006), Lemmon & Portniaguina (2006), Schmeling (2009). However, the relationship between sentiment and returns in each pair is not necessary due to a causal relationship. Rather, a relationship might exist as a result of common macro factors that drive both sentiment and returns (Jansen & Nahuis, 2003). The nature of the relationship between each pair is captured by Granger causality tests reported in Table 2.5.

Table 2.5 shows that market sentiment (Economy) Granger-causes both aggregate market and Financial sector returns. The significance of this relationship relies mainly on the Manufacturing sector sentiment that constitutes 40% of aggregate market sentiment. This finding is supported by the lack of significance of the rest of sentiment indices in causing aggregate market returns to change. In contrast, returns of the majority of sectors Granger-cause market sentiment. At sector level, causality runs in both directions with the exception of Retail Trade and Services industries for which causality only runs from returns to sentiment.

Table 2.5
p-values for Granger causality tests for sentiment and aggregate market and sector returns.

This table presents the p-value for Granger causality tests for sentiment indicators and stock return indices. The results cover the period from January 1985 to December 2014. r, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns					
	Market	Manufacturing	Construction	Retail Trade	Services	Financials
Economic and Consumer Confidence Indicators						
Economy	0.0173					0.0830
(r *g-cause sent*)	0.1342					0.1030
Consumer	0.6673	0.5800	0.7611	0.1662	0.2176	0.2078
(r *g-cause sent*)	0.0319	0.0225	0.2850	0.1544	0.3260	0.0117
Managerial sentiment						
Manufacturing	0.0003	0.0063				0.0479
(r *g-cause sent*)	0.0062	0.0399				0.0384
Construction	0.5479		0.0705			0.2762
(r *g-cause sent*)	0.3240		0.1018			0.5983
Retail Trade	0.8793			0.1622		0.7013
(r *g-cause sent*)	0.0069			0.0146		0.0057
Services	0.0992				0.0892	0.1795
(r *g-cause sent*)	0.0003				0.0135	0.0107
Services [wald test]	0.5055				0.1320	0.8143
(r *g-cause sent* [wald test])	0.0004				0.0346	0.0199

These results can be interpreted in two ways. Firstly, Manufacturing and Construction sectors are more prone to sentiment than Retail Trade and Services sectors. Therefore, risks associated with their sentiment are translated into returns. However, this interpretation is inconsistent with the "hard to value" argument of Baker & Wurgler (2007). The output of both Retail Trade and Services sectors are hard to measure (Doms et al., 2004; Mclaughlin & Coffey, 1990). Therefore, these sectors are more likely to be prone to fluctuations in sentiment than the Manufacturing and Construction sectors. Another way to interpret this result is that managerial sentiment indices are constructed by surveying firms rather than investors. Individual investors are subject to asymmetric information problems when valuing the companies in which they invest. Firms have more internal information. Hence, firm survey data on managerial sentiment would be expected to inform stock returns. Consequently, our results point to lower levels of information asymmetry and less uncertainty in valuation of stocks in Manufacturing and Construction sectors. Our data provides evidence of resolution of information asymmetry in those sectors. Expectations are less accurately reflected in stock returns in Services and Retail Trade sectors.

For Financial Services sector, results shown in Table 2.5 are consistent with the literature (such as Nejad & Huerta, 2014) in terms of the direction of causality. Nonetheless, the relationship is greatly affected by Manufacturing sector sentiment. These results reveal that the relationship between sentiment and stock market returns is not consistent across sectors. Where the aggregate sentiment of the market causes adjustment to stock returns, it is the different characteristics of the sector groupings that shapes the relationship.[7]

In Table 2.5, we also examine the association of consumer confidence with stock returns at aggregate and sector levels. Notably, consumer confidence is not

[7] Responses on sentiment survey contains information from companies based on their previous month performance. This may impact the relationship from returns to sentiment if returns are calculated using only the first 10 days. Therefore we repeated the analysis using the first 21 days and full month returns. The modifications had no impact on the results except for the Construction sector for which the relationship becomes insignificant when using full month returns.

found to Granger-cause stock returns in any of our tests while stock returns only Granger-cause consumer confidence in Manufacturing and Financials.

To further understand the nature of the return-sentiment relationship, we next turn our attention to the components of the sentiment surveys. We breakdown our causality tests by individual questions included in each sector survey. As shown in Table 2.6, questions explained how company respondents in each sector feel about past, present and future activities. Levels of confidence regarding prices and employment expectations are also considered.

Given the fact that stock returns reflect fundamentals of companies in each sector, we assume that stock returns explain company responses about their past activities. Respondents are aware of the performance of their firms in the past, which is reflected in stock returns. However, Construction sector projects have a longer time horizon than other sector groupings. For example, long time horizons to completion make judgment on performance more uncertain for companies and investors. The sentiment question in the survey focuses on judging the performance over a relatively short three-month horizon which may in part explain the inability of past returns to predict Construction sector sentiment.

Results shown in Table 2.6 indicate that stock returns have a significant impact on the expectations in the sector. Changes in stock returns cause adjustment to the expectation about the level of the employment in all sectors. However, returns have no effect on the expectations regarding selling prices in both Construction and Retail Trade sectors. Since stock returns mainly reflect company fundamentals, the development of expectations might be affected by availability bias. This implies that individuals assign greater weights to recent experience. Therefore, company expectations for the future of their activities explain how their stocks perform in the recent past.

In contrast, we find that sentiment Granger-causes returns for most of the sector groupings. Sentiment about production (order) expectations plays a significant role in causing the returns of the Manufacturing (Retail Trade) sectors. For the Construction sector, expectations about the employment level are associated

Table 2.6
p-values for Granger causality tests for survey questions and returns.

This table presents the p-value for Granger causality tests for sentiment indicators and sector return indices using individual survey questions. The results cover the period from January 1985 to December 2014. r, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Questions							
Manufacturing								
	Production trend observed in recent months	Assessment of order-book levels	Assessment of export order-book levels	Assessment of stocks of finished products	Production expectations for the months ahead	Selling price expectations for the months ahead	Employment expectations for the months ahead	Confidence Indicator (Q2 - Q4 + Q5) / 3
sent g-cause return	0.3300	0.0634	0.2654	0.7526	0.0584	0.4930	0.9956	0.0063
return g-cause sent	0.0188	0.0385	0.1231	0.0114	0.0398	0.0026	0.0022	0.0399
Construction								
	Building activity development over the past 3 months	Evolution of your current overall order books	Employment expectations over the next 3 months	Prices expectations over the next 3 months	Confidence Indicator (Q3 + Q4) / 2			
sent g-cause return	0.7873	0.0823	0.0014	0.1019	0.0705			
return g-cause sent	0.2057	0.2423	0.1010	0.9985	0.1018			
Retail Trade								
	Business activity (sales) development over the past 3 months	Volume of stock currently hold	Orders expectations over the next 3 months	Business activity expectations over the next 3 months	Employment expectations over the next 3 months	Prices expectations over the next 3 months	Confidence Indicator (Q1 - Q2 + Q4) / 3	
sent g-cause return	0.5907	0.2856	0.0522	0.3200	0.2664	0.6740	0.1622	
return g-cause sent	0.0210	0.5369	0.0626	0.0183	0.0396	0.1167	0.0146	
Services								
	Business situation development over the past 3 months	Evolution of the demand over the past 3 months	Expectation of the demand over the next 3 months	Evolution of the employment over the past 3 months	Expectations of the employment over the next 3 months	Expectations of the prices over the next 3 months	Confidence Indicator (Q1 + Q2 + Q3) / 3	
sent g-cause return	0.0831	0.0157	0.4882	0.1928	0.0857	0.1563	0.0892	
return g-cause sent	0.1218	0.1385	0.0356	0.0009	0.0002	0.0067	0.0135	
sent g-cause return†	0.2336	0.0009	0.3356	0.3924	0.1648	0.1325	0.1137	
return g-cause sent†	0.1733	0.0744	0.0299	0.0006	0.0003	0.0036	0.0346	

† refers to Wald test.

with highly significant changes in stock returns. However, for Services sector, expectations about the future appear to have no role in causing changes in stock returns. One explanation might be the uncertainty regarding future activities in the Services sector. Interestingly, company assessments of business activity development over the past three months, which reflects structural changes in the Service sector, shows a strongly significant impact on subsequent returns.

2.4.1 Robustness tests

2.4.1.1 Causality using FTSE100 Index, sectors return index and Managerial Sentiment Indicator (MSI)

The first set of robustness tests we conducted was to change the definition and construction of aggregate market returns and the aggregate sentiment index. Although, the five sector return indices constituents included 87.27% of the market capitalization of companies included in the FTSE All-Share, as a robustness check we substituted alternative indices of aggregate market returns.[8]

In addition to changing the definition of aggregate market returns, we reconstructed the Economical Sentiment Indicator (ESI) using only four sectoral sentiment indicators after the exclusion of consumer confidence indicator (CCI). As discussed earlier, CCI represents 20% of the ESI, therefore elimination will result in a pure Managerial Sentiment Indicator (MSI). The weights of the four sectors in the MSI are adjusted *pro rata* to their original values in the ESI. Consequently, the MSI is used as an aggregate sentiment index.[9]

We then repeated the analysis using FTSE 100 Index and an equally weighted return index (RI 5-sectors) that contains the five previously constructed sector return indices. In order to match the same sectors included in the ESI and the

[8] The other 12.63% represents the Utilities and Health Care sectors which we excluded when constructing sectors return indices. Although the NACE Rev. 2 classification includes utility and health care activities, sentiment surveys do not. Hence, we exclude Utilities and Health Care from sector return indices.

[9] The calculation of indicators' weights to construct the MSI are described in details in Appendix 5.

MSI, we created another index (RI 4-sectors) that encompasses all sector return indices except Financial Services sector. As reported in Table 2.7, results show no significant sensitivity to the change of returns definition. The results using different indices indicate some very small differences to the FTSE All Share results. Significance levels are largely unchanged for sentiment granger-causes returns. The one notable difference being that Construction returns grange-cause sentiment in the RI 5-sectors and RI 4-sectors indices.

Table 2.7
Granger causality tests using different sentiment and return indices.

This table presents the p-values for testing the sentiment-return relationship using alternative definitions for aggregate market return index and the managerial sentiment indicator. RI 5 Sector is an equally weighted return index of Manufacturing, Construction, Retail Trade, Services and Financial Services sectors. RI 4 Sector represents the same sectors as in RI 5 Sector except the Financial Services sector. The results cover the period from January 1985 to December 2014. r, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns Indices			
	FTSE-ALL	FTSE 100	RI 5 Sector	RI 4 Sector
Economic and Consumer Confidence Indicators				
Economy (ESI)	0.0173	0.0724	0.0059	0.0059
(r *g-cause sent*)	0.1342	0.1324	0.0441	0.0523
Consumer	0.6673	0.9339	0.2790	0.5731
(r *g-cause sent*)	0.0319	0.0256	0.0200	0.0900
Managerial sentiment				
Managerial Sentiment Index	0.8236	0.0650	0.0288	0.0412
(r *g-cause sent*)	0.0233	0.0907	0.0291	0.0458
Manufacturing	0.0003	0.0024	0.0031	0.0019
(r *g-cause sent*)	0.0062	0.0099	0.0136	0.0418
Construction	0.5479	0.5598	0.3700	0.2274
(r *g-cause sent*)	0.3240	0.3262	0.0462	0.0186
Retail Trade	0.8793	0.8588	0.8877	0.7743
(r *g-cause sent*)	0.0069	0.0102	0.0015	0.0021
Services	0.0992	0.1214	0.1696	0.5326
(r *g-cause sent*)	0.0003	0.0002	0.0045	0.0009
Services [wald test]	0.5055	0.5100	0.6900	0.7000
(r *g-cause sent* [wald test])	0.0004	0.0004	0.0085	0.0110

2.4.1.2 Causality during different periods

We further examine the predictability of managerial sentiment before and after two major stock market crises; the dotcom bubble and the GFC.[10] As can be seen by comparison of Tables 2.8 to 2.11, our main findings remain unchanged for the dotcom bubble and the GFC periods. As before, this implies that the sentiment associated with Manufacturing industry significantly affects both sector and aggregate market returns. However, the reverse does not hold in either period. This could be explained by increased attention to stock prices as a result of the dotcom period. It is also worth noting that the EC Manufacturing questionnaire includes producers of technological products which explains the increased significance of Manufacturing sentiment in predicting stock market returns for the post-dot com period. Additionally, the insignificance of Construction and Consumer confidence in predicting aggregate market returns is also confirmed for the dotcom bubble.

Similarly, results before and after the GFC, as shown in Tables 2.10 and 2.11, provide some interesting differences in results. The sentiment associated with both the Manufacturing sector and the Construction sector become more significant in predicting aggregate market returns after the crisis. This result could reasonably be assumed to reflect the impact of the sub-prime crisis on the sensitivity of the market to changes in these sectors. Sentiment in the Retail Trade sector appears to be marginally significant in the pre-crisis period but insignificant in the post-crisis period. Therefore, although beyond the goals of our study, the response of asset returns to sentiment around financial crises could further be investigated using non-linear models previously used by studies such as (Guidolin et al., 2014; Maasoumi & Racine, 2002; McMillan, 2001)

Ferrer et al. (2016) examined CCI as a measure of investor sentiment before and after the dotcom and the GFC meltdowns. Notably, their findings show that, unlike the US, CCIs have an insignificant relationship with the stock market in

[10] Since the Services sector indicator is only available starting from April 2006, we are unable to examine the relationship for earlier periods.

Table 2.8
p-values for Granger causality tests for aggregate market and sectoral levels (*pre*-dotcom collapse).

This table presents the p-value for Granger causality tests for sentiment indicators and stock return indices for the *pre*-dotcom crisis. The results cover the period from January 1985 to December 1999. r, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns				
	Market	Manufacturing	Construction	Retail Trade	Financials
Economic and Consumer Confidence Indicators					
Economy	0.8236				0.7705
(r *g-cause sent*)	0.0233				0.0111
Consumer	0.5266	0.1052	0.509	0.7169	0.6338
(r *g-cause sent*)	0.2956	0.0021	0.5057	0.7647	0.183
Managerial sentiment					
Manufacturing	0.0333	0.0084			0.1400
(r *g-cause sent*)	0.2042	0.5103			0.0346
Construction	0.9772		0.2845		0.9872
(r *g-cause sent*)	0.2894		0.0861		0.7617
Retail Trade	0.0486			0.3532	0.2119
(r *g-cause sent*)	0.1587			0.0101	0.1126

Table 2.9
p-values for Granger causality tests for aggregate market and sectoral levels (*post*-dotcom collapse).

This table presents the p-value for Granger causality tests for sentiment indicators and stock return indices for *post*-dotcom crisis. The results cover the period from January 2003 to December 2014. r, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns				
	Market	Manufacturing	Construction	Retail	Financials
Economic and Consumer Confidence Indicators					
Economy	0.0464				0.0725
(*r g-cause sent*)	0.0794				0.2461
Consumer	0.1457	0.2704	0.9617	0.2608	0.4312
(*r g-cause sent*)	0.0487	0.3504	0.9530	0.7625	0.2324
Managerial sentiment					
Manufacturing	0.0026	0.0084			0.0222
(*r g-cause sent*)	0.0299	0.1859			0.0092
Construction	0.4369		0.7641		0.5079
(*r g-cause sent*)	0.1160		0.1889		0.062
Retail Trade	0.0560			0.7627	0.6438
(*r g-cause sent*)	0.0679			0.2009	0.1594

Table 2.10
p-values for Granger causality tests for aggregate market and sectoral levels (*pre*-GFC).

This table presents the p-value for Granger causality tests for sentiment indicators and stock return indices for *pre*-GFC. The results cover the period from January 1985 to December 2006. *r*, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns				
	Market	Manufacturing	Construction	Retail Trade	Financials
Economic and Consumer Confidence Indicators					
Economy	0.8539				0.9470
(*r g-cause sent*)	0.0175				0.0070
Consumer	0.7442	0.1832	0.7409	0.3268	0.4616
(*r g-cause sent*)	0.0351	0.0017	0.0454	0.1059	0.014
Managerial sentiment					
Manufacturing	0.1139	0.0698			0.2912
(*r g-cause sent*)	0.1809	0.2598			0.0251
Construction	0.8192		0.1382		0.9222
(*r g-cause sent*)	0.6183		0.2608		0.8392
Retail Trade	0.0828			0.1588	0.4355
(*r g-cause sent*)	0.0081			0.0000	0.0467

Table 2.11
p-values for Granger causality tests for aggregate market and sectoral levels (*post*-GFC).

The table presents the p-value for Granger causality tests for sentiment indicators and stock return indices for *post*-GFC. The results cover the period from January 2010 to December 2014. *r*, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	Returns				
	Market	Manufacturing	Construction	Retail Trade	Financials
Economic and Consumer Confidence Indicators					
Economy	0.3257				0.0272
(*r g-cause sent*)	0.0255				0.0470
Consumer	0.9999	0.9960	0.4643	0.3301	0.9981
(*r g-cause sent*)	0.9987	0.0598	0.7722	0.7172	0.9981
Managerial sentiment					
Manufacturing	0.0137	0.0466			0.8876
(*r g-cause sent*)	0.8204	0.5268			0.4288
Construction	0.0278		0.2262		0.8924
(*r g-cause sent*)	0.3348		0.8473		0.6189
Retail Trade	0.8964			0.9885	0.7597
(*r g-cause sent*)	0.9998			0.6766	0.9937

the EU. Hence, our results are consistent with their conclusion that CCIs are an inappropriate measure of investor sentiment, at least in the UK market, where individual investors participate less actively and less directly in stock market trading compared to the US.[11]

2.5. Conclusion

In this study, we examine the association between managerial sentiment with aggregate UK market returns and returns for five sector groupings. Using time series of UK sector and market return indices and managerial and business confidence indicators obtained from European Commission (EC), we provide evidence that managerial sentiment is an effective predictor of aggregate and sector stock returns. Our measure of consumer confidence is not a predictor of sector or aggregate returns. However, aggregate stock returns and Manufacturing returns predict consumer confidence in our tests.

We find evidence, both for FTSE-ALL share index and FTSE 100 index, that the predictive power of sentiment is sector dependent. For all aggregate sentiment measures, we find strong evidence of co-movement with the market but little evidence of short-run predictability in returns. Additionally, our results confirm that sentiment has a significant effect on aggregate UK stock returns over the period and that sentiment is a significant predictor of expected returns on average. For sector groupings, we find that stock market returns are mainly affected by the sentiment associated with the Manufacturing and Construction sector groupings. Further, we demonstrate that sentiment associated with the Retail Trade and Services sector groupings have no predictive power for stock returns.

[11] Individual investors in the UK own 12% of the value of equity shares traded in the stock market compared to 37.3%in the US. For the UK, the figure is obtained from the Office of National Statistics(ONS) available at http://www.ons.gov.uk, accessed on 20 May 2016. For the USA, the figure is obtained from the Federal Reserve available at http://www.federalreserve.gov, accessed on 20 May 2016.

In order to examine how the characteristics of each sector affect the sentiment-returns relationship, we also collected data from the questions included in sectoral surveys. Notably, our analysis of answers to survey questions suggests that the specific issues that drive the sentiment-return relationship differ between sectors. While expectations about productions and order levels predict returns in both Manufacturing and Retail Trade sectors, employment expectations constitute an important factor in predicting Construction sector returns. In contrast, sentiment for lagged business development sentiment is more significant in the Services sector. These results support our general conclusion that the strength and significance of the relationship between sentiment and stock returns varies between sectors.

Taken together, the findings of this study have implications for practitioners, policy-makers, regulators and portfolio managers whose decisions depend on and/or are affected by movements of stock prices. Our evidence indicates that sector-specific sentiment influences stock returns and stock returns in turn affect investor sentiment, in the form of consumer confidence and managerial sentiment. However, the relationship varies across sectors. For practitioners, our results suggest that asset allocation and fund management strategies might take account of both managerial sentiment and their impact on sector returns. Such information might be obtained by scrutinizing channels of information from management to markets such as trading statements, corporate reports, news announcements and interviews with managers. Regulators might consider how their policies with respect to capital and credit allocation might be received by managers in particular sectors. Such sentiment, in our study at least, affects stock pricing and thus contributes to pricing anomalies which can have serious consequences for investors and markets. Further research might consider how sector-specific sentiment contributes to pricing bubble formation or, from a more pecuniary perspective, how to exploit the effects identified in this chapter in a trading strategy.

Appendix 1: Sample questions of sectors surveys

1- Manufacturing confidence indicator

Q. Do you consider your current overall order books to be...?

[more than sufficient , sufficient , not sufficient]

Q. How do you expect your production to develop over the next 3 months? It will...

[increase, remain unchanged, decrease]

2- Construction confidence indicator

Q. Do you consider your current overall order books to be...?

[more than sufficient (above normal), sufficient (normal for the season), not sufficient (below normal)]

Q. How do you expect your firm's total employment to change over the next 3 months? It will...

[increase, remain unchanged, decrease]

3- Services confidence indicator and financial services confidence indicator

Q. How has your business situation developed over the past 3 months? It has ...

[improved, remained unchanged, deteriorated]

Q. How do you expect the demand (turnover) for your company's services to change over the next 3 months? It will...

[increase, remain unchanged, decrease]

4- Consumer confidence indicator

Q. How do you expect the financial position of your household to change over the next 12 months? It will...

[get a lot better, get a little better, stay the same, get a little worse, get a lot worse, don't know]

Q. How do you expect the general economic situation in this country to develop over the next 12 months? It will...

[get a lot better, get a little better, stay the same, get a little worse, get a lot worse, don't know]

Q. How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...

[increase sharply, increase slightly, remain the same, fall slightly, fall sharply, don't know]

Q. Over the next 12 months, how likely is it that you save any money?

[very likely, fairly likely, not likely, not at all likely, don't know] Retail trade confidence indicator

Appendix 2: Construction of confidence indicators

Confidence indicators are calculated using *Scores* that summarize replies to surveys questions. Percentage of responses to any single question should follow:

$$PP + P + E + N + NN + M = 100 \tag{2.5}$$

where:

PP is very positive, P is positive, E is neutral, N is negative, NN is very negative and M is without any opinion.

Scores then are calculated as:

$$Score = (PP + \frac{1}{2}P) - (\frac{1}{2}N + NN) \tag{2.6}$$

The score of a question is ranged from -100 if all respondents choose the negative option to +100 if all respondents choose the positive option. Scores are seasonally adjusted using "Dainties" as the seasonal-adjustment algorithm. For each sector, the confidence indicator is the simple arithmetic average of all seasonally adjusted scores of questions.

Appendix 3: Autocorrelation function for level and differenced series

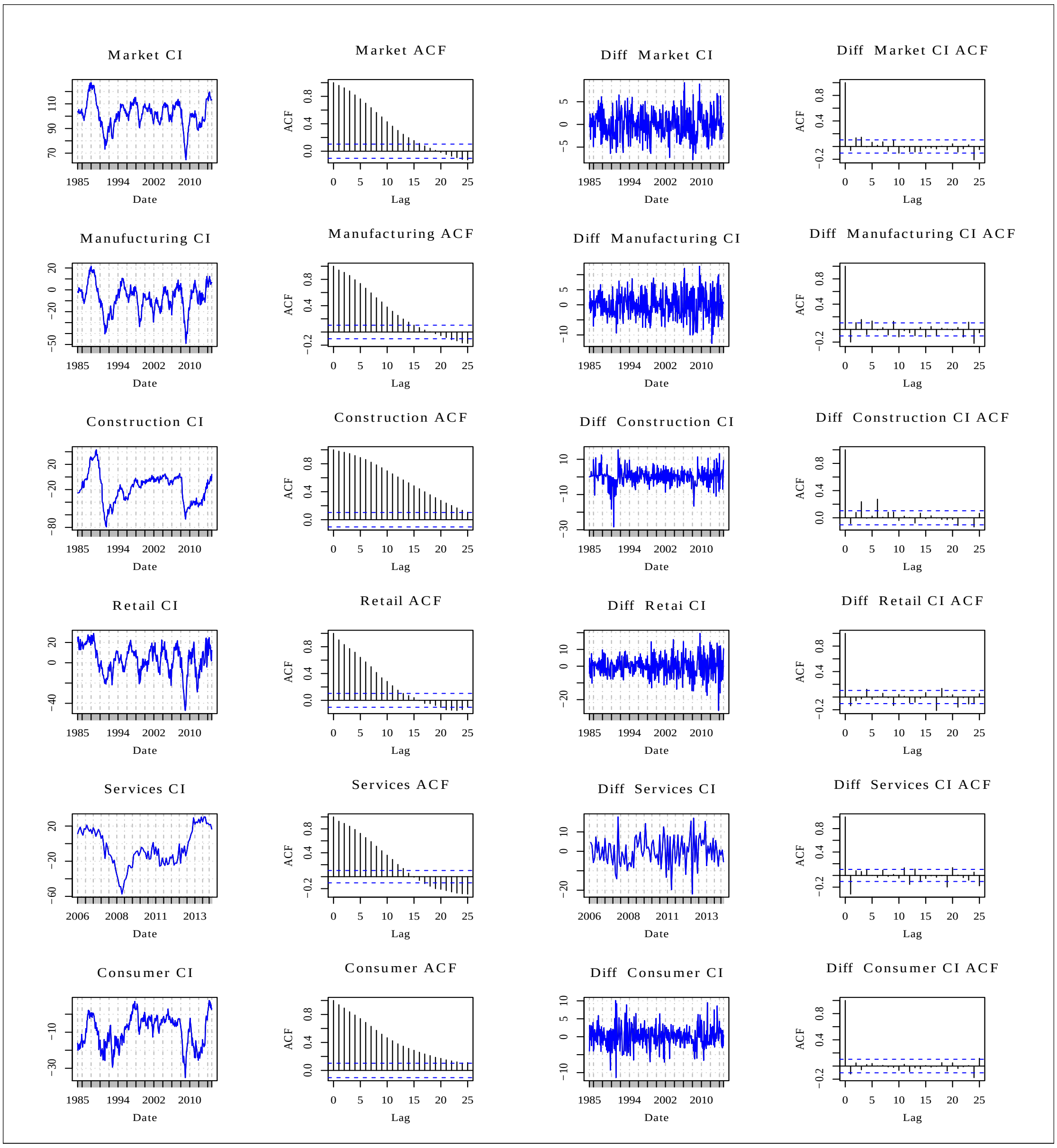

Figure 2.5: Correlogram of confidence indicators at both level and differenced values

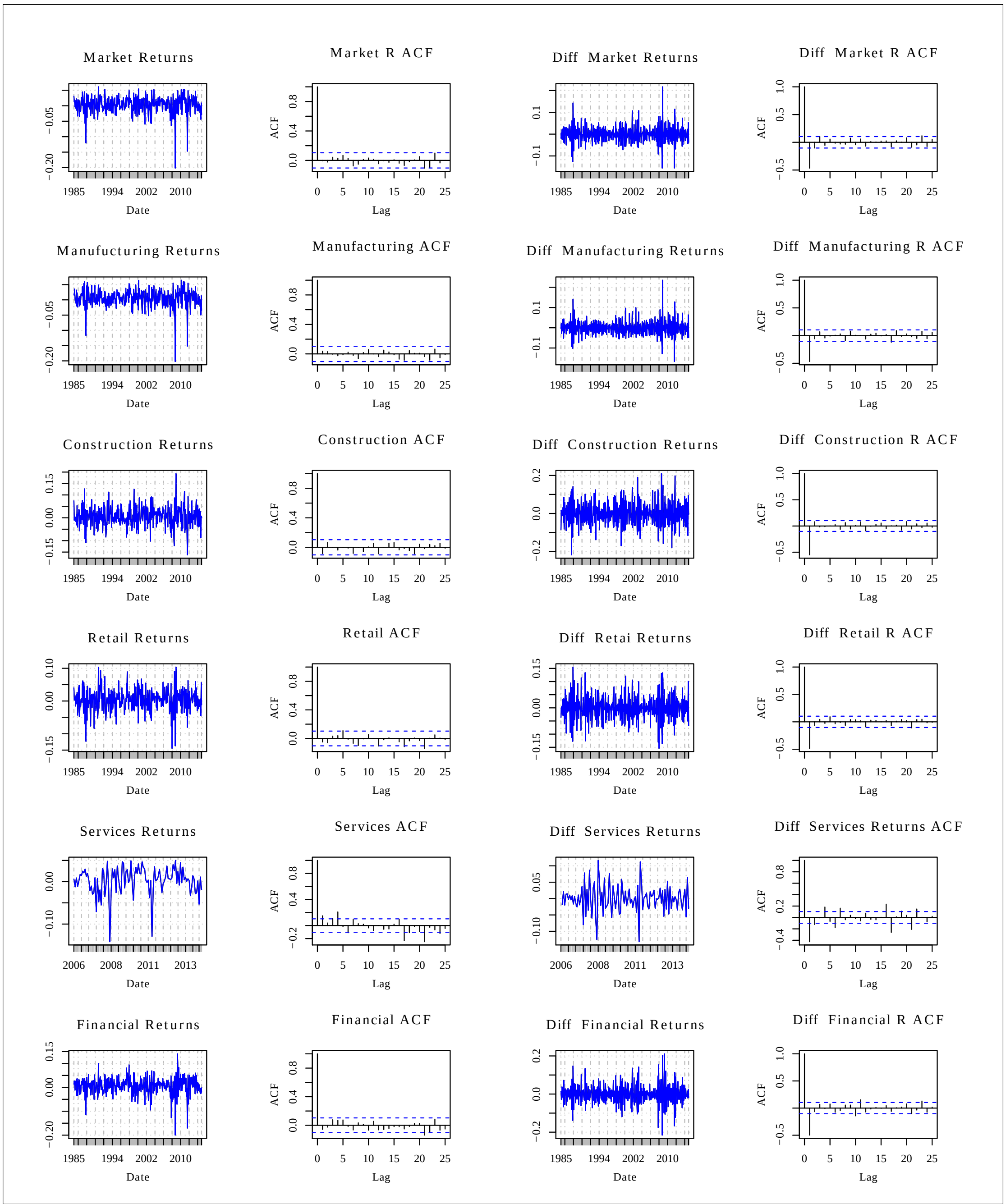

Figure 2.6: Correlogram of returns at both level and differenced values

Appendix 4: Cross-correlation function between sentiment indices and returns

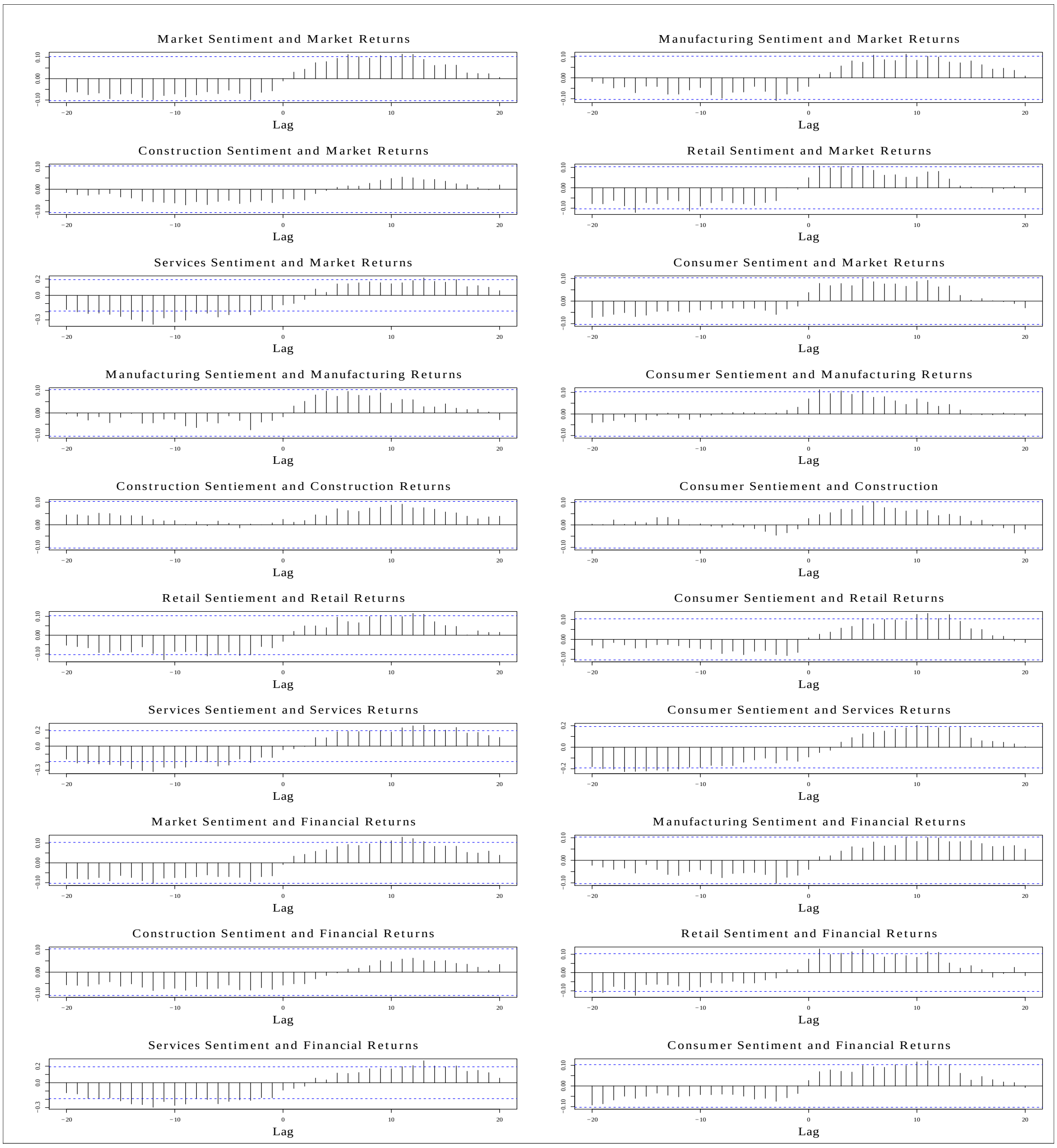

Figure 2.7: Sentiment and returns cross correlation function

The x and y axes represents the number of lags used and the correlation coefficient respectively. The graph shows the correlation between investor sentiment $Sent_{t+k}$ and stock returns R_t . Positive lags on the x axis means R leads $Sent$ and the negative lags means $Sent$ leads R. The dashed line shows the 5 % significance level.

Appendix 5: Construction of the Managerial Sentiment Indicator (MSI)

The Managerial Sentiment Indicator (MSI) covers four business surveys of the Economic Sentiment Indicator (ESI). The original weights of indicators in the ESI are 40% to Manufacturing, 30% to Services, 20% Consumer and 5% for each of the Retail Trade and Construction indicators. After the exclusion of the consumer confidence indicator, we redistribute the 20% *pro rata* based on the original distribution. This results in 50% to Manufacturing, 37.5% to Services, and 6.25% for each of the Retail Trade and Construction indicators.

For the Services sector, the indicator has no values until April 2006. Therefore, the MSI is constructed using only three sectors for the period from January 1985 to March 2006. The percentage redistributed to the weights of the three sectors is 50% (%20 from the consumer confidence indicator and 30% from the Services indicator). The weights for this period are 80% to Manufacturing, 10% to each of the Construction and Retail Trade indicators. These adjustments maintain the ratio of Services weight to Manufacturing weight at 0.75 and Construction and Retail Trade weights to Manufacturing weight at 0.125 for ESI and MSI. Following the same methodology used by the EC in constructing the ESI, the MSI is scaled to have a mean of 100 and a standard deviation of 10.

Chapter 3

Sentiment Transmission between Managers and Investors

3.1. Introduction

Investor sentiment has received a substantial attention in finance literature since Statman & Solt (1988) studied the usefulness of The Bearish Sentiment Index published by Investor Intelligence. They argued that the power of the index in forecasting stock returns is not better than what can be predicted by chance. They claimed that existence of errors in investors' cognition is what justifies persistence reliance on the index by investors. However, a subsequent strand of studies concerned with how investor sentiment is measured provided evidence on how it affects stock market returns (Abraham et al., 1993; Baker & Wurgler, 2006; Da et al., 2015; Lee et al., 1991). Furthermore, Salhin et al. (2016) argued that managerial sentiment predicts aggregate market and sector returns and the prediction power depends primarily on characteristics of each sector grouping. In this chapter, we build on Salhin et al. (2016) study by constructing a composite managerial sentiment index based on significant characteristics of four sector groupings which we call Core Managerial Sentiment Index (CMSI). We used the index to test its performance in predicting stock market returns compared to competing indices of investor sentiment. In addition, we test the transmission between managerial and investor sentiments and more importantly, we provide evidence on the polarity of sentiment transmitted from managers to investors.

Studying the impact of investor sentiment on finance and investment decisions raises a question of how to measure investor sentiment. Since investor sentiment is not directly observable, it has been measured using several proxies including closed-end fund discount, mutual fund flow, investor surveys, volatility indices and composite sentiment indices (Baker & Wurgler, 2006; Frazzini & Lamont, 2008; Lee et al., 1991; Whaley, 2000). Other studies used consumer confidence as another possible measure for investor sentiment (Fisher & Statman, 2003; Jansen & Nahuis, 2003; Otoo, 1999; Schmeling, 2009). They showed how consumer confidence can negatively forecasts stock market returns and they argued for its appropriateness as a measure of investor sentiment. However, Ferrer et al. (2016) argued that consumer confidence is an inappropriate proxy for investor sentiment. Their finding is also confirmed by Salhin et al. (2016) who showed that consumer confidence lacks the predictive power of stock market returns. However, they provided evidence on the performance of managerial sentiment as a better predictor of aggregate market and sector returns.

In our view, using investor, consumer and managerial sentiments interchangeably provides misleading and confusing results. Individuals are distinct in their nature and the process of aggregating their sentiments is based on common characteristics they share as consumers, managers or investors. The overlap between agent groups provides an appealing justification to use their measure of sentiment interchangeably since all managers and investors are consumers and some managers could be also investors and vice versa. This overlap is also confirmed by the correlation between sentiment/confidence indicators related to each agent as in Salhin et al. (2016) and in what we report in a subsequent section. However, the majority of information gathered from each group when polling for their opinions or when monitoring their investment behavior is different. For example, while investor surveys focus on evaluation of stock market performance, consumer surveys enquire about consumer prices and managerial surveys are more concerned with business activities.[1] In addition, there are different factors that affect sentiment of each group of market participants. For instance, Tetlock (2007) shows that media content, such as news about the stock market, influences investor sentiment. Alternatively, Lahiri & Zhao (2013) show that media news is less important in determining consumer sentiment than their expectations about economy, prices, income and unemployment.

Moreover, using market participant sentiment indicators interchangeably diminishes the possibility of studying how they relate and impact each other. According to Baker & Wurgler (2013), managers tend to cater for investor sentiment through various corporate actions. For instance, evidence shows that managers use *pro forma* earnings disclosures and other corporate activities to cater for investor sentiment. (see, e.g., Baker et al. (2003); Brown et al. (2012); Cooper et al. (2001)).

In this chapter, we define managerial sentiment as judgment about business conditions that is expressed through managers' feelings. We distinguish between investor and managerial sentiment to achieve two main objectives. The first objective is to test the strength of managerial sentiment in predicting stock market returns compared to investor sentiment. Our expectation is that managerial sentiment is a better predictor of stock returns since managers have informed opinions on prospects of their businesses compared to investors. Our second objective is to test whether managerial sentiment is transmitted to investors and, if so, whether the transmission is asymmetric between positive and negative sentiment.

The rest of the chapter is structured as follow: section 2 reviews relevant literature. Section 3 presents data and summary statistics. In section 4, we compare the predictive power of managerial sentiment and several proxies for investor sentiment. Section 5, we investigate the relationship between investor and managerial sentiment. Section 6 investigates the asymmetric sentiment transmission from managers to investors. Section 7 concludes.

[1] Qiu & Welch (2006) provide discussion on investor sentiment surveys. More information on consumer and business surveys is available in the Joint Harmonized EU Programme of Business and Consumer Surveys guide available at http://ec.europa.eu, accessed on 27 January 2017.

3.2. Literature review

3.2.1 Investor sentiment

Rationality of individual behaviour is a central assumption in theories of financial market economics. Efficient Market Hypothesis (EMH) by Fama (1970) is one theory that assumes investor rationality. It claims that prices in the market are accurate and reflect all available information about assets. If prices are driven away from their fundamental values, arbitrageurs are able to exploit the difference between current and fundamental prices and bring prices back to equilibrium. On the other hand, early studies of investor sentiment such as Bondt (1998); Lee et al. (1991); Sanders et al. (1997) consider arbitrage to be costly and not profitable. Thus, assets will be consistently mispriced.

Furthermore, some anomalies in the financial market cannot be understood under the traditional EMH. One of these anomalies is the closed-end funds discount puzzle. Closed-end funds are traded class of assets whose share price is determined by forces of demand and supply. These funds invest in different classes of assets along with bearing some liabilities. The net value of funds' assets and liabilities called "net asset value" or NAV. According to the EMH, share prices of closed-end funds should almost equal its NAV per share to reflect all available information about the fund. However, there is usually a difference known as the discount. Lee et al. (1991) argue that closed-end fund discount is a reflection of investor sentiment in the market. They find that movement of closed-end fund discounts is correlated with small companies' stocks held by individual investors whose decisions are more likely to be affected by sentiment. Their result has been supported by work of Bodurtha et al. (1995); Chen et al. (2003); Noronha & Rubin (1995).

Baker & Wurgler (2007, p. 129) defined investor sentiment as "a belief about future cash flows and investment risks that is not justified by facts at hand". If investors base their investment decisions on this belief, asset prices will be driven away from their fundamental values. Furthermore, investor sentiment costs the market by increasing probability of bubble formation. For example, Alan Greenspan, former chairman of the US Federal Reserve used the term “Irrational Exuberance” to warn of the formation of dot.com bubble (Shiller, 2015). Zouaoui et al. (2011) shows that investor sentiment increases the likelihood of a stock market crisis. In addition, Berger & Turtle (2015) confirm a link between investor sentiment and asset bubbles.

Various studies of investor irrationality have investigated the relationship between stock market returns and changes in investor sentiment. These studies have produced two notable results. First is the identification of measures which proxy for the true unobservable level of sentiment. Second is the identification of the shape of the relationship between investor sentiment and stock returns. Examples of these studies are (Abraham et al. (1993); Baker & Wurgler (2006); Beaumont et al. (2008); Chang et al. (2007); Eichengreen & Mody (1998); Fisher & Statman (2000); Lee et al. (1991); Neal & Wheatley (1998); Statman & Solt (1988); Wang (2003)).

Measures of investor sentiment used to examine its impact on financial markets include closed-end fund discount Lee et al. (1991), investor and consumer surveys (Bathia et al. (2016); Hwang (2011); Jansen & Nahuis (2003); Lemmon & Portniaguina (2006); Otoo (1999); Schmeling (2009)), mutual fund flows (Bathia & Bredin (2013); Brown et al. (2003); Frazzini & Lamont (2008)), and volatility index (Nikkinen & Vähämaa (2010); Whaley (2000)). In addition, some studies have used composite sentiment indices that combine different measures (Baker & Wurgler (2006); Brown & Cliff (2004)). Using these measures, stock market returns are found to be affected by aggregate investor sentiment in the market.

3.2.2 Managerial sentiment

The debate of rationality vs irrationality has also taken its place in studying managers’ decisions. The notion of “smart managers’ refers to claims that managers are able to identify any mispricings that is created by irrational investor. Baker & Wurgler (2013) supported these claims in several ways; for example, managers possess superior information on their own businesses, therefore they can distinguish fundamental value of their shares from observed market price. In addition, they can impact share prices through manufactured information that affects investors demand. On contrary, Ben-David et al. (2013) show that top financial managers are "severely miscalibrated" in the sense that they systematically underestimate the range of stock market returns as well as prospects of their own firms. Furthermore, studies show that managers, like investors, are prone to several behavioural biases such as overconfidence (e.g., Ben-David et al. (2013); Hribar & Yang (2015); Malmendier & Tate (2005, 2008); Pikulina et al. (2017)), disposition effect (e.g., Crane & Hartzell (2010)), anchoring (e.g., Baker & Wurgler (2013)), and loss-aversion (e.g., Shefrin (2001)).

Measures of managerial sentiment/optimism have varied across studies. Salhin et al. (2016) used a survey based measure of managerial sentiment developed by the European Commission. They found that managerial sentiment is a good predictor of stock returns at an aggregate and sectors level. In particular, they found that the aggregate sentiment-return relationship is mainly driven by sentiment associated with the Manufacturing industry. Moreover, Jiang et al. (2015) developed a managerial sentiment index by quantifying the textual tone of financial statements and conference calls. They showed that managerial sentiment outperforms investor sentiment and macroeconomic factors in predicting stock market returns.

3.2.3 Catering theory

Baker & Wurgler (2013) define catering as "any actions intended to boost share prices above fundamental value". Under catering theory, managers deliberately involve in activities that affect investors short term demand. For example, Subramanyam (1996) finds a positive correlation between unexpected accruals and stock returns. Managers are found to use discretionary accruals as signals of private information to investors. Furthermore, Hribar et al. (2017) examined the relationship between managerial sentiment and accrual estimates. They observe that estimates for loan loss provisions are negatively associated with managerial sentiment. However, Louis & Robinson (2005) argue that findings regarding the association between managerial sentiment and discretionary accruals do not indicate deliberate actions from managers to influence investors' decisions. Rather they indicate that managerial actions are unintentionally affected by the level of optimism that managers have towards future earnings and do not indicate any opportunism. Nevertheless, their argument does not fit corporate disclosures that managers report voluntarily. For example, Brown, Christensen. Elliott (2006) found that managers are likely to report favorable *pro forma* earnings measures in periods with higher levels of investor sentiment. In addition, they show that managers' catering for investor sentiment is more noticeable for companies whose stock prices are more prone to sentiment. Furthermore, if corporate actions are determined by managerial sentiment and do not intended to cater for investor sentiment, we would expect no impact of market sentiment on firms' management. However, Bochkay & Dimitrov (2014) provided an evidence on the impact of investor sentiment on managerial sentiment. They found that investor sentiment explains 37.7% of the variation in managerial sentiment and managers are likely to be optimistic (pessimistic) when investor sentiment is high (low). Such findings are in support of the catering theory that managerial actions are intended to affect short-term pricing of companies' stocks.

3.3. Data and preliminary tests

3.3.1 Investor sentiment

To test our expectations of the predictive power and symmetry of transmission of managerial sentiment, we use the closed-end fund discount (CEFD), the number of initial public offerings (NIPOs) and the FTSE 100 Volatility Index (VFTSEIX) as proxies for investor sentiment.

3.3.1.1 Closed-end fund discount (CEFD)

Performance of closed-end funds is mainly determined by the value of their net assets (total assets minus total liabilities) which is disclosed on a per share basis called Net Asset Value (NAV). However, closed-end fund shares are traded for a price that is determined by forces of supply and demand. The difference between NAV and price per share is called a discount which provides an indicator of investors sentiment towards the stock market.

Following Lee et al. (1991) we calculated a monthly value-weighted index of discounts (CEFD) as follow:

$$CEFD_t = \sum_{i=1}^{n_t} W_i \; DISC_{it}, \tag{3.1}$$

where, $W_i = \frac{NAV_{it}}{\sum_{i=1}^{n_t} NAV_{it}}$, NAV_{it} is the net asset value of fund i at the end of month t.

$DISC_{it}= \frac{NAV_{it}- \; P_{it}}{NAV_{it}} \; X \; 100$, P_{it} is the share price of fund i at the end of month t.

n_t is the number of funds with available P and NAV at the end of month t.

As reported in Table 3.1, the average discount for the UK is 7.1% indicating lower investor sentiment towards the stock market during the period from January 2000 to September 2014.

3.3.1.2 Number of initial public offerings (NIPOs)

Investor sentiment is often associated with the demand for initial public offerings. Higher number of initials public offerings indicates investors' enthusiasm and vice versa. Data for IPOs is obtained from London Stock Exchange with total number of 2054 IPOs for our entire sample period, with low figures during and after the financial crisis of 2008-2009 as shown in Figure 3.1.

Table 3.1
Descriptive statistics sentiment, returns and macroeconomic indices.

Data covers the period from January 2000 to September 2014 for the UK market. Sentiment indices are closed-end fund discount (CEFD), UK stock market volatility (VFTSEIX), number of Initial Public Offerings (NIPOs), and core managerial sentiment index (CMSI). FTSE100, FTALLSH and FTSESCO represent excess returns of FTSE100, FTSE All Share and FTSE SmallCap indices above the three-month interest rate. Market return index calculated as the weighted average returns of all UK listed companies in each month minus the three-month interest rate. Term-spread is the difference in yields between 10-Year governmental bonds and 3-Month Treasury bill (T-bill). IPT, INF, GDP are percentage change in industrial production level, inflation rate and GDP growth rate, respectively.

Panel A: Sentiment						
	mean	sd	median	trimmed	min	max
NIPOs	11.6	10.48	8.00	10.1	0.00	52.00
CEFD	7.10	2.75	6.98	7.00	1.47	15.54
VFTSEIX	2.94	0.37	2.92	2.93	2.29	3.85
CMSI	95.48	12.00	98.3	96.88	55.1	111.8
Panel B: Returns						
	mean	sd	median	trimmed	min	max
FTSE100	-2.57	5.04	-2.28	-2.50	-17.38	11.96
FTALLSH	-2.51	5.07	-2.26	-2.42	-17.33	11.66
FTSESCO	-2.36	6.04	-1.81	-2.21	-23.27	25.17
Market	-1.70	4.70	-1.90	-1.77	-11.31	8.55
Panel C: Macro-economic Indices						
	mean	sd	median	trimmed	min	max
T-bill	2.97	2.15	3.82	2.96	0.23	5.96
Term-spread	1.09	1.31	0.93	1.02	-0.71	3.60
IPT	-0.07	0.98	0.00	-0.03	-4.68	2.60
INF	2.23	1.07	2.00	2.13	0.50	5.20
GDP	0.44	0.66	0.57	0.54	-2.20	1.42

3.3.1.3 FTSE100 Volatility Index (VFTSEIX)

Volatility Index *(VFTSEIX)* is the implied standard deviation of options on FTSE100 Index. *VFTSEIX* represents how certain or uncertain investors are about stock market volatility, with higher values indicate low sentiment or pessimistic investor. Measures of investor sentiment are highly correlated as shown in Table 3.2.

3.3.2 Managerial sentiment

We use managerial sentiment data from business surveys provided by the European Commission on monthly basis and conducted nationally by the Confederation of British Industry (CBI) and Experian (EXP). We obtain survey data that covers the period from January 2000 till September 2014 for four sectors groupings namely Manufacturing, Construction, Retail Trade, and Services.

Salhin et al. (2016) provide evidence on the impact of managerial sentiment on stock market returns across different sectors. They show that the sentiment-returns relationship is sensitive to distinct characteristics of each sector. For example, while managerial expectations regarding production/order levels are important predictors of sector returns in Manufacturing and Retail Trade sectors, forecasting power of expectations about employment levels is strong in Construction sector. We use their results to select survey questions in order to construct a Core Managerial Sentiment Index (CMSI) that reflect significant characteristics of each sector. Details on the construction of the CMSI is provided in details in Appendix 1.

3.3.3 Return indices

To compare the impact of investor and managerial sentiment on stock market returns, we use FTSE100, FTSE All Share (FTALLSH) and FTSE SmallCap (FTSESCO) indices. We included FTSESCO Index as smaller companies are expected to be more prone to investor sentiment than bigger companies (Baker & Wurgler, 2006). In addition to the three indices, we construct a value-weighted return index (Market) by incorporating data for all UK companies - including listed and delisted companies - to minimize the impact of survivorship bias. Returns are

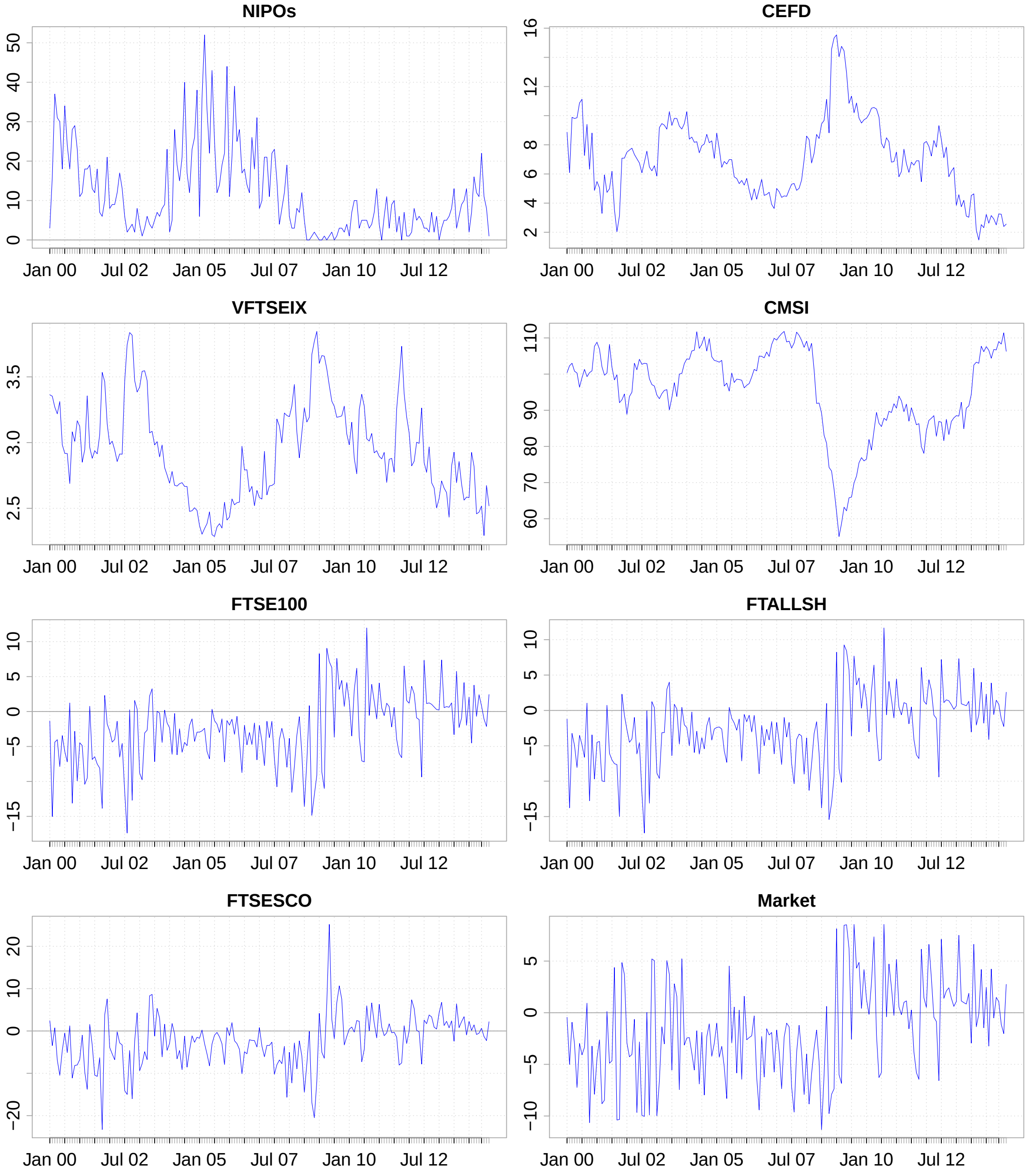

Figure 3.1: Sentiment and stock market return indices

All indices are monthly data covers the period from January 2000 to September 2014. Sentiment indices are NIPOs is the number of initial public offerings, CEFD is the closed-end fund discount, VFTSEIX is the implied volatility of options on FTSE100 Index. Stock returns indices are FTSE100, FTSE All Share, FTSE SmallCap and Market index represent all companies listed on London Stock Exchange in each month.

Table 3.2

Correlation for sentiment, returns and macroeconomic indices.

Data covers the period from January 2000 to September 2014 for the UK market. Sentiment indices are closed-end fund discount (CEFD), UK stock market volatility (VFTSEIX), number of Initial Public Offerings (IPOs), and core managerial sentiment index (CMSI). FTSE100, FTALLSH and FTSESCO represent excess returns of FTSE100, FTSE All Share and FTSE SmallCap indices respectively. Market return index calculated as the weighted average returns of all UK listed companies in each month minus the three-month interest rate. Term-spread is the difference in yields between 10-Year and 3-Month Treasury bill (T-bill). IPT, INF, GDP are percentage change in industrial production level, inflation rate and GDP growth rate, respectively.

Panel A: Correlations between sentiment and return indices

	NIPOs	CEFD	VFTSEIX	CMSI	FTSE100	FTALLSH	FTSESCO
CEFD	-0.22**						
VFTSEIX	-0.48***	0.50***					
CMSI	0.49***	-0.64***	-0.47***				
FTSE100	-0.19*	0.05	-0.29***	-0.27***			
FTALLSH	-0.18*	0.05	-0.29***	-0.27***	0.99***		
FTSESCO	-0.16*	0.06	-0.27***	-0.25***	0.82***	0.86***	
Market	-0.22**	0.09	-0.17*	-0.33***	0.92***	0.93***	0.82***

Panel B: Correlations between sentiment and macroeconomic indices

	NIPOs	CEFD	VFTSEIX	CMSI	T-bill	Term-spread	IPT	INF
T-bill	0.56***	-0.06	-0.08	0.59***				
Term-spread	-0.55***	0.22**	0.20**	-0.63***	-0.92***			
IPT	0.06	-0.12	-0.13	0.09	0.00	-0.01		
INF	-0.37***	0.09	0.09	-0.44***	-0.48***	0.42***	-0.09	
GDP	0.27***	-0.43***	-0.34***	0.49***	0.14	-0.15*	0.26***	-0.49***

Panel C: Correlations between returns and macroeconomic indices

	FTSE100	FTALLSH	FTSESCO	Market	T-bill	Term-spread	IPT	INF
T-bill	-0.51***	-0.51***	-0.45***	-0.50***				
Term-spread	0.45***	0.45***	0.41***	0.47***	-0.92***			
IPT	0.04	0.05	0.03	0.03	0.00	-0.01		
INF	0.17*	0.16*	0.06	0.14	-0.48***	0.42***	-0.09	
GDP	0.08	0.09	0.16*	0.06	0.14	-0.15*	0.26***	-0.49***

Level of significance for correlation coefficients are ***:0.01, **:0.05, *:0.1.

winsorized at 0.5% level to remove the effect of outliers. Return indices, stock prices and market value data are obtained from Datastream for the period from January 2000 to September 2014.

3.3.4 Macroeconomic variables

We use a set of macroeconomic series as control variables when testing the relationship between sentiment indicators. Variables include three-month treasury bill (T-bill), Term spread; defined as the difference between the yield on 10 years government bonds and T-bill, change in total index of production (IPT), inflation (INF) and GDP growth rate (GDP). Monthly data on macroeconomic variables are obtained from Datastream except GDP which is only available in quarterly form. Therefore, we use polynomial interpolation to transform GDP data into monthly figures. Figure 3.2 illustrates macroeconomic variables and details on data sources are provides on Table 3.3.

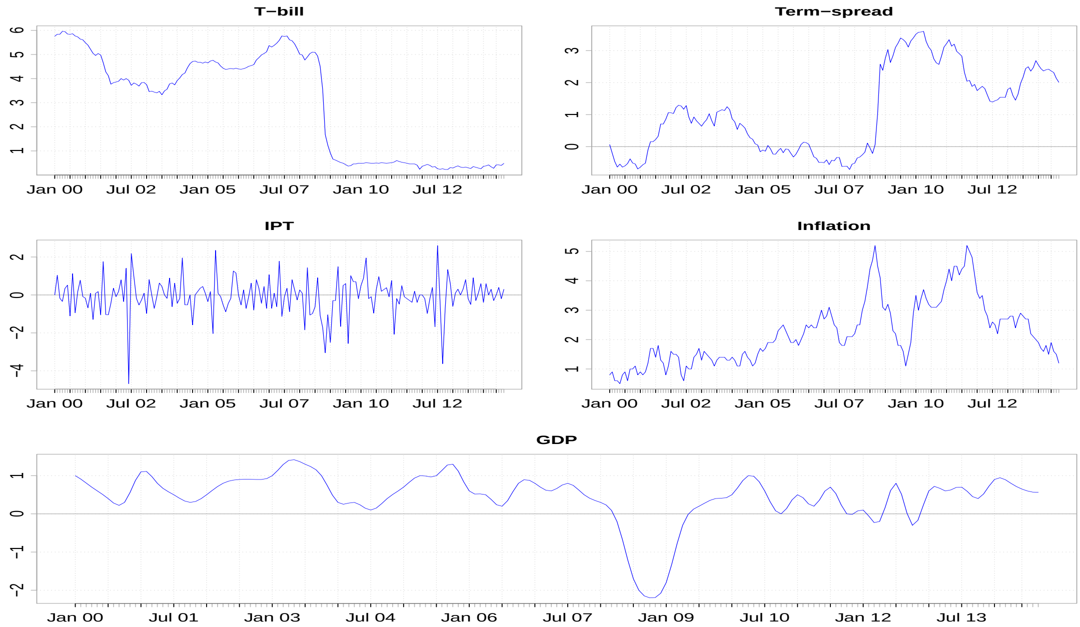

Figure 3.2: Macroeconomic indices

All indices are monthly data covers the period from January 2000 to September 2014. Term-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT, INF, GDP are percentage change in industrial production level, inflation rate and the GDP growth rate, respectively.

Table 3.3
Data sources of investor and managerial sentiment, stock returns and macroeconomic variables

Variables	Data Sources	Notes
Closed-end fund discount (CEFD)	Datastream	Data on prices and net asset value are obtained on all UK investment companies on each month including funds that disappeared on subsequent months to minimise survivorship bias.
Number of IPOs (NIPOs)	London Stock Exchange	Data include the IPOs issued for the main UK market (1384 IPOs), the AIM market (655 IPOs) and Specialist Fund Segment (5 IPOs).
FTSE100 Volatility Index (VFTSEIX)	Datastream	Data type on Datastream is "VFTSEIX".
Core Managerial Sentiment Index (CMSI)	European Commission	Although the index covers only 4 sectors (Manufacturing, Construction, Retail Trade and Services), classification of economic activities in the European Community (NACE Rev. 2) covered by those sectors overlaps with other industries covered by the Industrial Classification Benchmark [2].
Return Indices	Datastream	Total number of companies used to construct the Market return index equals 7370 company over the sampling period.
Macroeconomic variables	Datastream	Our choice of macro variables follows Schmeling (2009).

3.3.5 Preliminary tests

We examine whether sentiment, returns and macroeconomic time series are unit-root non-stationary using Augmented Dickey-Fuller (ADF), Philips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Table 3.4 reports all tests for level and differenced data. Test of non-stationary has shown the following series are unit root non-stationary: CEFD, CMSI, T-bill, Term-spread, and INF. Other series are stationary and have *I(0)* order. The impact of test results on specifications of our models will be discussed in details in subsequent sections.

Table 3.4
Unit root tests.

Tests are based on 360 observations for all variables except Services sector which has 104 observations. Models used for unit root test specified to include the intercept with lags of the variable. Lag length for Augmanted Dicky-Fuller (ADF) tests are determined by Akaike Information Criterion with maximum of twelve lags differences. Newey-West procedure is used to calculate bandwidths for both Philips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. For spectral estimation, Bartlett's kernel is used.

	Level			Differenced		
	ADF	PP	KPSS	ADF	PP	KPSS
IPOs	-4.5948	-6.2035	0.4898	-17.7861	-24.1278	0.0141
CEFD	-1.9086	-2.5327	0.1478	-11.1586	-18.4326	0.0400
VFTSEIX	-3.2394	-3.2494	0.1330	-11.3000	-14.7949	0.0274
CMSI	-1.5832	-1.9255	0.3155	-8.5204	-14.6146	0.1115
FTSE100	-6.8787	-10.8835	0.8715	-16.7236	-34.5728	0.0046
FTALLSH	-6.8179	-10.6134	0.8369	-16.6984	-33.1240	0.0048
FTSESCO	-6.9119	-8.9355	0.6194	-16.3741	-24.2538	0.0075
Market	-7.1764	-11.0787	0.7590	-17.8065	-33.5390	0.0045
T-bill3M	-1.3388	-1.0462	1.0140	-5.6253	-6.8106	0.2430
T-Spread	-1.5800	-1.4032	0.7073	-7.8906	-9.7342	0.1356
IPT	-10.7194	-16.2513	0.0559	-18.0769	-41.8966	0.0025
INF	-2.2437	-2.3008	0.8495	-7.9032	-11.3632	0.1608
GDP	-5.4574	-2.8496	0.2516	-12.6999	-4.8027	0.0994

[2] More details are available in the Joint Harmonized EU Programme of Business and Consumer Surveys guide available at http://ec.europa.eu, accessed on 27 January 2017.

3.4. Investor sentiment, managerial sentiment and stock returns

For interest of comparison, we test the relationship between investor sentiment, managerial sentiment and stock returns by employing the following Granger causality model (Granger, 1988):

$$Ret_t = \alpha_r + \sum_{i=1}^{k} \beta_{ri} Ret_{t-i} + \sum_{i=1}^{k} \gamma_{ri} \Delta Sent_{t-i} + \varepsilon_{rt}, \tag{3.2}$$

$$\Delta Sent_t = \alpha_s + \sum_{i=1}^{k} \beta_{si} \Delta Sent_{t-i} + \sum_{i=1}^{k} \gamma_{si} Ret_{t-i} + \varepsilon_{st}, \tag{3.3}$$

where Ret_t denotes returns at time t; $Sent_t$ is investor/managerial sentiment indicator at time t; Δ is the first difference of the series; k is the maximal lag; and ε_{rt} is an error term. Sentiment (Sent) Granger-causes returns if returns (Ret) can be better predicted using histories of both sentiment and returns than by using history of returns alone.

As shown in Table 3.5, all sentiment indicators predict stock market returns, however, their predictive power is sensitive to the return index used. CEFD can only predict FTSE SmallCap return index. The results are not surprising since fund discounts tend to co-move with small companies share prices (Lee et al., 1991). On the other hand, results for IPOs is affected by the performance of firms that exited the market since it only predicts the Market index. Furthermore, findings indicate that our managerial sentiment index (CMSI) outperform investor sentiment indicators across all stock market return indices, particularly FTSE

SmallCap Index[3]. These results highlight the importance of managerial "informed-sentiment" compared to investors sentiment in predicting stock market returns.

Table 3.5
p-values for Granger causality tests for sentiment and aggregate market returns.

This table presents the *p*-value for Granger causality tests for sentiment indicators and stock return indices. The results cover the period from January 2000 to September 2014. *r*, *g-cause*, and *sent* denote return, Granger-cause, and sentiment, respectively.

	FTSE100	FTALLSH	FTSESCO	Market
IPOs	0.5642	0.5049	0.4967	0.0260
(*r g-cause sent*)	(0.7403)	(0.7610)	(0.5204)	(0.9473)
CEFD	0.7211	0.5800	0.0684	0.7434
(*r g-cause sent*)	(0.0051)	(0.0049)	(0.0002)	(0.0123)
VFTSEIX	0.0009	0.0020	0.1479	0.0004
(*r g-cause sent*)	(0.7910)	(0.7979)	(0.4309)	(0.9178)
CMSI	0.0024	0.0013	0.0000	0.0028
(*r g-cause sent*)	(0.0261)	(0.0228)	(0.2889)	(0.1440)

3.5. The relationship between managerial and investor sentiments

In this section, we start analysing the relationship between managerial and investor sentiments. In fact, the relationship between managerial and investor sentiments run in both directions through catering and market timing mechanisms. According to Baker & Wurgler (2013), catering refers to managerial actions intended to drive share prices above their fundamental values (e.g dividend declaration, corporate reports, press release...etc.). On the contrary, market timing refers to managerial decisions intended to take advantage of temporary mispricing by issuing (repurchasing) overvalued (undervalued) shares. Since market timing

[3] FTSE SmallCap consists of companies that their sizes are not large enough to qualify them to be included in the FTSE350. Since managers' surveys are conducted on a sample of 3550 companies according to Salhin et al. (2016), we conclude that majority of this sample are businesses which their size corresponds to the size of FTSE SmallCap constituents. More information on the construction of FTSE indices are available at http://www.ftse.com, accessed on 3 February 2017.

theory mainly concerns with managers' financing decisions which are not covered by managerial sentiment surveys, we focus only on the direction from managerial sentiment to investor sentiment. We used VFTSEIX as our measure of investor sentiment based on its performance in predicting majority of our return indices as shown in Table 3.5.

Baker & Wurgler (2013) and Schmeling (2009) used a set of control variables to roll out the impact of macro risk factors while estimating the relationship between investor sentiment and stock returns. We followed the same approach to examine the impact of managerial sentiment on investor sentiment. Specifically, we employed a vector autoregressive model with exogenous variables (VARX) to include short-term interest rates (T-bill), term spread (Term-spread), unemployment rate (UNEMP), total industrial production (IPT), inflation (INF), and growth rate of gross domestic product (GDP). In addition, we added stock market return index (FTSE100) as an explanatory variable to control for investor sentiment that results from current and past performance of the stock market. The VARX model translates into:

$$SENT_t = \phi_0 + \sum_{i=1}^{p} \phi_i CMSI_{t-i} + \sum_{j=0}^{s} \beta_j \psi_{t-j} + \upsilon_t, \tag{3.4}$$

where $SENT_t$ is investor sentiment at time t measured by the volatility index (VFTSEIX), $CMSI_{t-i}$ is managerial sentiment index at time t-i, ψ_{t-j} is a matrix includes macro variables and stock market return index, ϕ_0 is and intercept and ϕ_i is VAR coefficients, β_j is κ x m coefficient matrices, and υ_t is the disturbance term. The orders p and s are non-negative integers denote number of lags for endogenous and exogenous variables and are determined by the sequential Chi square test of Tiao and Box (1981).

Results in Table 3.6 show a significant impact of managerial sentiment on investor sentiment. The influence of managerial sentiment on investor sentiment could follow either of two scenarios; the first is that investors form their sentiment based on rational expectations on prospects of their investments in isolation of managerial sentiment. Similarly, managerial sentiment is also based on rational expectations but with a time advantage due to managers' ability to access business information. Therefore, the impact of managerial sentiment on investor sentiment under this scenario is illusionary and it exist only due to an "information lag" between investors and managers. A challenge to this scenario lies in the common definition of investor sentiment as a belief about future cash flows and risks that is not supported by facts at hand (Baker & Wurgler, 2007). Consequently, investor sentiment is not formed based on rational expectations or fundamental news. Furthermore, if investor sentiment is based on fundamental information, we would expect it to have no significant impact on stock market returns according to the Efficient Market Hypothesis (Fama, 1970).

Table 3.6
Effects of Managerial sentiment on investor sentiment

Figures represents results from vector autoregressive model with exogenous variables (VARX). Variables are investor sentiments (SENT), managerial sentiment (CMSI), stock market return index (FTSE100), short-term interest rates (T-bill), term spread (Term-spread), total industrial production (IPT), inflation (INF), and growth in gross domestic product (GDP). Lags for the model are determined by the sequential chi square test of Tiao and Box (1981) for multivariate timer series.

	Dependent Variable: Investor Sentiments (SENT_t))			
	Estimate	Standard Error	t-stat	p-value
Intercept	-0.8991	0.2154	-4.1743	0.0000
$CMSI_{t-1}$	-0.0039 †	0.0014	2.6965	0.0077
$SENT_{t-1}$	0.7711	0.0367	20.9998	0.0000
FTSE100	0.0263	0.0025	10.3317	0.0000
T-bill	0.0776	0.0873	0.8886	0.3754
Term-spread	0.0521	0.0691	0.7542	0.4517
IPT	0.0146	0.0115	1.2728	0.2048
INF	0.0219	0.0358	0.6100	0.5426
GDP	0.0521	0.0641	0.8137	0.4169
$FTSE100_{t-1}$	0.0026	0.0027	0.9306	0.3533
$T\text{-}bill_{t-1}$	-0.0759	0.0883	-0.8596	0.3912
$Term\text{-}spread_{t-1}$	-0.0859	0.0685	-1.2544	0.2114
IPT_{t-1}	0.0089	0.0112	0.7951	0.4276
$Inflation_{t-1}$	-0.0306	0.0370	-0.8280	0.4088
GDP_{t-1}	-0.0774	0.0644	-1.2018	0.2311

†Negative coefficient means a positive relationship between managerial and investor sentiment since the proxy for investor sentiment (VFTSEIX) has a reverse relationship with sentiment.

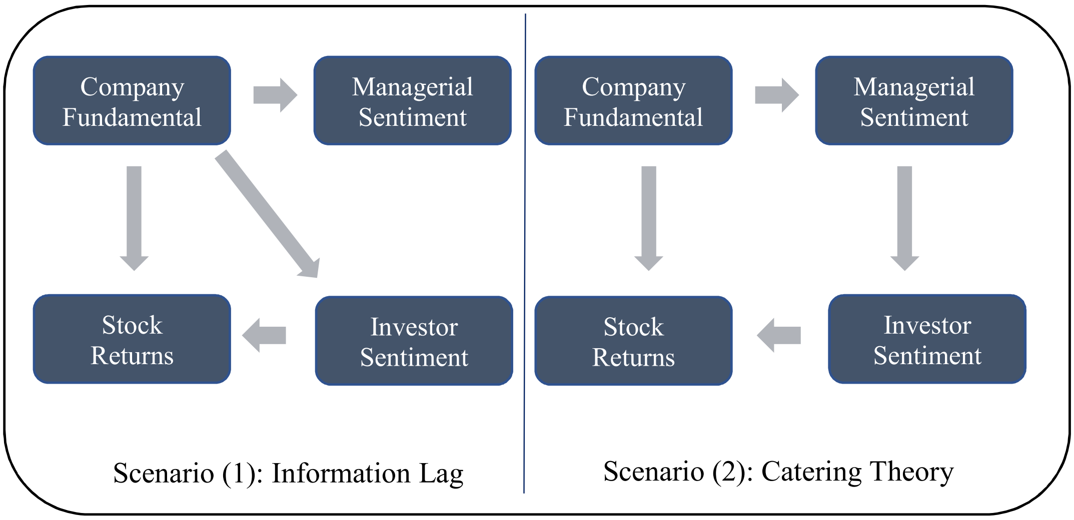

Figure 3.3: Illustration of the path from company fundamentals to stock market returns.

The second scenario is that managers send signals to investors through various corporate actions, i.e. catering for investor sentiment. In catering theory, Baker & Wurgler (2013) argued that managers' goal is to cater for short-term investors demand in attempt to influence any temporary mispricing. Therefore, this scenario provides an evidence on the success of managers in achieving their 'catering" goals. In addition, it offers more justification to the impact of managerial sentiment on stock returns since managers do not directly trade in the stock market, and if they do, their ability to affect stock prices is minimal compared to investors. We provide an illustration of the path from information and sentiment to stock market returns for both scenarios in Figure 3.3.

3.6. Asymmetric sentiment transmission from managers to investors

As a robustness test and to further examine the relationship between managerial and investor sentiment, we used a composite measure of investor sentiment. Baker & Wurgler (2006) argued that individual measures of investor sentiment include components that is related to sentiment as well as other idiosyncratic,

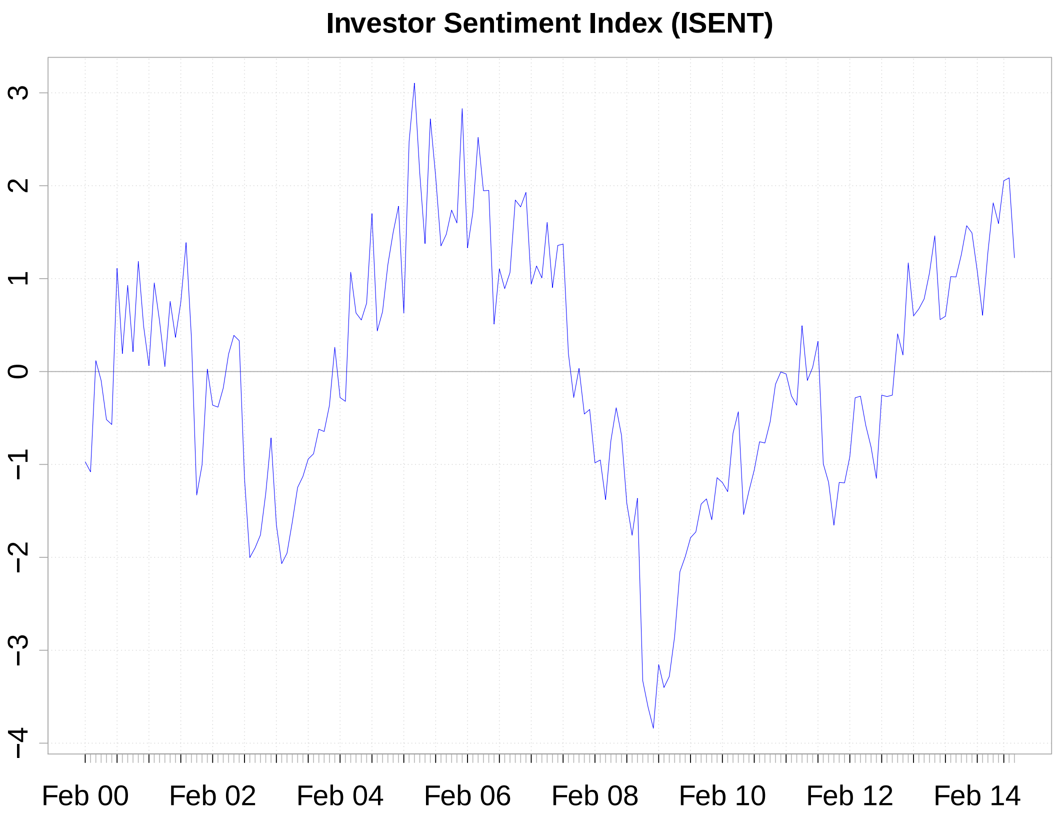

Figure 3.4: A composite measure of investor sentiment

The measure is constructed using Principal Component Analysis (PCA) of the Number of Initial Public Offerings (NIPOs), Closed-end Fund Discount (CEFD), and Volatility Index (VFTSEIX).

non-sentiment components. They used principal component analysis (PCA) to construct a composite measure of investor sentiment which reflects the common sentiment-related component of different measures. We follow their methodology to construct an investor sentiment index (ISENT) from NIPOs, CEFD, and VFTSEIX measures. Details on the methodology applied are provided in Appendix 2.

As shown in Figure 3.4, our composite index demonstrates same pattern reflected by the underlying measures of sentiment as well as the core managerial sentiment index (CMSI). The correlation between ISENT and CMSI is 0.69 and it is statistically significant at 1% significance level. To examine the relationship between investor and managerial sentiment we started by applying unit root tests on ISENT. Similar to CMSI, results show that ISENT is a unit root non-stationary series $I(1)$ indicating the possibility that both series share a common stochastic trend. Therefore, we extended our preliminary tests to examine the possibility of co-integration between CMSI and ISENT. Results of Johansen (1991) procedure and Phillips & Ouliaris (1990) cointegration tests indicate that a combination of CMSI and ISENT follow a stationary path and have a long-run relationship.

Balke & Fomby (1997) argued that symmetric cointegration model is misspecified if there is an asymmetric adjustment to long-run equilibrium (LRE). Furthermore, we expect managers cater to investor sentiment if only they possess positive information/sentiment towards the future of their businesses. In other words, we predict that investor sentiment has an asymmetric response to positive and negative managerial sentiment. Therefore, we consider a graphical representation to obtain guidance on the symmetry of the relationship between investor and managerial sentiment indices. Figure 3.5 indicates an asymmetric behavior of the relationship between investor and managerial sentiment indices. As shown by the figure, there is a difference in the magnitude of CMSI and ISENT in periods when they share same level of sentiment. It shows also a difference in the speed of adjustments of sentiment indices as indicated by the sharpness of peaks in positive and negative areas. Therefore, we examined two types of asymmetry namely; “Deepness” and “Steepness” in order to test the asymmetric relationship between CMSI and ISENT. According to Sichel (1993), deepness refers to the difference between positive or negative shocks in the magnitude of divergence from equilibrium (i.e. how far ISENT diverge from LRE after a positive/negative shock from CMSI). Steepness refers to the difference in speed of adjustment of the economic variable after positive or negative shocks (i.e. how long does it take ISENT to converge to LRE after a positive/negative shock from CMSI). While deepness is tested by the threshold autoregressive model (TAR) developed by Enders & Granger (1998), steepness is tested by the momentum threshold autoregressive model (MTAR) developed by Enders & Siklos (2001).

To estimate TAR and MTAR models, we start by estimating the LRE relationship as in the first step of Engle & Granger (1987) two-step methodology:

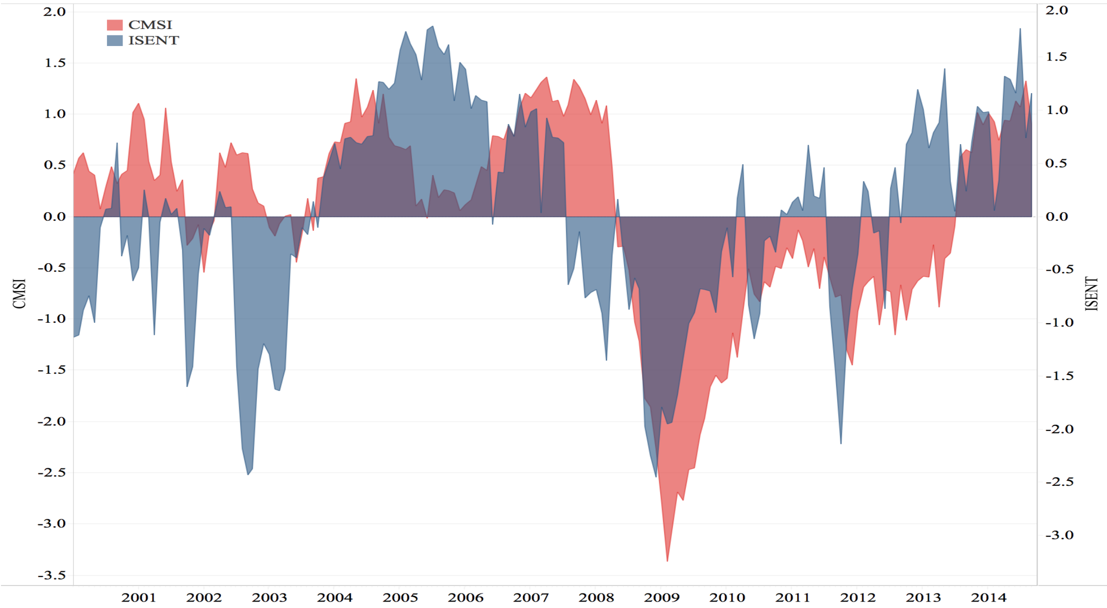

Figure 3.5: An area plot of managerial sentiment vs investor sentiment indices

Each index is scaled to have a mean of zero and standard deviation of 1.

$$ISENT_t = \beta_0 + \beta_1\, CMSI_t + \mu_t, \tag{3.5}$$

where $ISENT_t$ is investor sentiment indicator, $CMSI_t$ is managerial sentiment indicator, β are the estimated parameters and μ_t is the disturbance term. $ISENT_t$ and $CMSI_t$ are $I(1)$ non-stationary series. The following TAR model is employed to examine the asymmetric adjustment to the LRE relationship:

$$\Delta\mu_t = I_t\; \rho_1\; \mu_{t-1} + (1 - I_t)\; \rho_2\; \mu_{t-1} + \sum_{\iota=1}^{p} \gamma_p \Delta\mu_{t-p} + \xi_t \tag{3.6}$$

where μ_t is the residual term from Equation (3.5), ρ_1 and ρ_2 are speed of adjustment coefficients to test both cointegration and asymmetry in the LRE relationship, $\Delta\mu_{t-p}$ is the first difference of the residual term at time $t-p$ where

p is the lag length which is determined using Akaike Information Criterion (AIC), ξ_t is the disturbance term and I_t is the Heaviside indicator function such that:[4]

$$I_t = \begin{cases} 1, & \mu_{t-1} \geq \tau \\ 0, & \mu_{t-1} < \tau \end{cases} \quad , \textit{ and } \tau \textit{ is the threshold }^{5} \tag{3.7}$$

The expected sign for ρ_1 and ρ_2 in Equation 6 is negative to indicate the adjustment if μ_{t-1} is above or below its LRE relationship. The model tests the null hypothesis of whether $\rho_1 = \rho_2$, and if rejected, the adjustment to divergence is asymmetric. If $\rho_1 > \rho_2 >$ -1, the positive regime of sentiment is more persistent than a negative regime, assuming magnitudes of positive and negative shocks are equal. In MTAR specification, the adjustment rate depends on changes in the residuals in which the I_t is the Heaviside indicator function will be:

$$I_t = \begin{cases} 1, & \Delta\mu_{t-1} \geq \tau \\ 0, & \Delta\mu_{t-1} < \tau \end{cases} \quad , \textit{ and } \tau \textit{ is the threshold} \tag{3.8}$$

where $\Delta\mu_{t-1}$ is the first difference of the residuals. In MTAR model, if $\rho_1 > \rho_2 >$ -1, positive phase tends to be more persistent than a negative regime irrespective of the disequilibrium magnitude. Results of TAR and MTAR models are presented in Tables 7 and 8, respectively.

As reported by Table 3.7 and 3.8 , contemporaneous relationship between managerial sentiment (CMSI) and investor sentiment (ISENT) is positive and highly significant. Results for TAR model suggest that the long run relationship between ISENT and CMSI is statistically significant at 10% significance level even after considering disequilibrium magnitudes that result from positive or negative shocks. However, the results do not support the existence of a deepness asymmetry in the LRE relationship between CMSI and ISENT. On contrary, results

[4] The reason for including the $\Delta\mu_{t-p}$ term is that residuals from Equation 5 are not characterised by a white noise process and are serially correlated.

[5] We followed Chan (1993) procedures to determine the threshold value. We fitted the regression model in Equation 3.6 for all possible threshold values and selected the value that minimises the sum of squared error of the model.

Table 3.7
TAR (deepness asymmetry) results

LR reports results for Equation 3.5, where the long-run relationship between managerial sentiment (CMSI) and investor sentiment (ISENT) is estimated. CI reports results for Equation 3.6 where the asymmetric cointegration is examined. As the table reports the findings of threshold autoregressive model (TAR), identification of the Heaviside indicator function is provided in Equation 3.7. Lag length for residuals is determined using Akaike information criterion (AIC).

		LR: Dependent Variable: Investor Sentiment ($ISENT_t$) CI: Dependent Variable: Differenced Residuals ($\Delta\mu_t$)			
		Estimate	Standard Error	t-stat	p-value
LR	(Intercept)	-7.522	0.596	-12.627	0.000***
LR	$CMSI_t$	0.079	0.006	12.726	0.000***
CI	μ^{+}_{t-1}	-0.187	0.064	-2.925	0.004***
CI	μ^{-}_{t-1}	-0.038	0.079	-0.487	0.627
CI	$\Delta\mu_{t-1}$	-0.237	0.085	-2.785	0.006***
CI	$\Delta\mu_{t-2}$	-0.258	0.085	-3.044	0.003***
CI	$\Delta\mu_{t-3}$	-0.159	0.081	-1.969	0.051*
CI	$\Delta\mu_{t-4}$	0.006	0.077	0.081	0.935

Cointegration: φ tatistic for H_0: $\rho_1 = \rho_2 = 0$ equals 4.2807, p-value: 0.0154*
Asymmetry: F statistic for H_0: $\rho_1 = \rho_2$ equals 2.4736, p-value: 0.1177

Levels of significance are ***:0.01, **:0.05, *:0.1.

for MTAR models suggests the rejection of the null hypothesis of no cointegration at 1% significance level as indicated by the value of φ statistic. The findings also support the existence of steepness asymmetry in the LRE relationship. Such results mean that investor sentiment rapidly adjust to positive shocks from managerial sentiment than negative shocks with approximately 20% each month to converge to the long-run equilibrium relationship between them. They also mean that managers pay more attention to high investor sentiment regimes than low investor sentiment regimes. Although the divergence of investor sentiment from the LRE relationship after a negative shock from managerial sentiment is statistically insignificant, it may imply that investors are more likely to react, or even panic, to abnormal deviations in periods characterised by low sentiment. The speed of such mania is beyond what managers can resolve so it persists for a period of time until the market restores its previous sentiment status.[6] In other words, formation of financial bubbles is slower than panic from financial crises.

[6] These results are apparent in Figure 3.5; the troughs are sharper than peaks.

Table 3.8
MTAR (steepness asymmetry) results

LR reports results for Equation 3.5 where the long-run relationship between managerial sentiment (CMSI) and investor sentiment (ISENT) is estimated. CI reports results for Equation 3.6 where the asymmetric cointegration is examined. As the table reports the findings of momentum threshold autoregressive model (MTAR), identification of the Heaviside indicator function is provided in Equation 3.8. Lag length for residuals is determined using Akaike Information Criterion (AIC).

		LR: Dependent Variable: Investor Sentiment (ISENT_t) CI: Dependent Variable: Differenced Residuals ($\Delta\mu_t$)			
		Estimate	Standard Error	t-stat	p-value
LR	(Intercept)	-7.522	0.596	-12.627	0.000***
LR	CMSI_t	0.079	0.006	12.726	0.000***
CI	μ^+_{t-1}	-0.200	0.057	-3.522	0.001***
CI	μ^-_{t-1}	0.126	0.100	1.261	0.209
CI	$\Delta\mu_{t-1}$	-0.247	0.084	-2.947	0.004***
CI	$\Delta\mu_{t-2}$	-0.249	0.083	-3.004	0.003***
CI	$\Delta\mu_{t-3}$	-0.155	0.079	-1.962	0.051*
CI	$\Delta\mu_{t-4}$	0.032	0.075	0.422	0.674

Cointegration: φ statistic for H_0: $\rho_1 = \rho_2 = 0$ equals 7.6649, p-value: 0.0006***
Asymmetry: F statistic for H_0: $\rho_1 = \rho_2$ equals 9.0046, p-value: 0.0031**

Levels of significance are ***:0.01, **:0.05, *:0.1.

After establishing the asymmetric cointegration between investor and managerial sentiment indices, we investigated short-run dynamics of their relationship. We used an asymmetric threshold vector error correction model (ATVECM) to understand whether positive or negative managerial sentiment is transmitted differently to investor sentiment. Our model is specified as follow:

$$
\begin{aligned}
\Delta ISENT_t = \Gamma_0 &+ \sum_{i=1}^{p} \Gamma_1^+ \; \Delta ISENT^+_{t-p} + \sum_{i=1}^{p} \Gamma_2^+ \; \Delta CMSI^+_{t-p} \\
&+ \sum_{i=1}^{p} \Gamma_1^- \; \Delta ISENT^-_{t-p} + \sum_{i=1}^{p} \Gamma_2^- \; \Delta CMSI^-_{t-p} \\
&+ \; I_t \Phi_1^+ ECT^+_{t-1} + \; (1 - I_t) \; \Phi_1^- ECT^-_{t-1} + \; \nu_t
\end{aligned}
\tag{3.9}
$$

where, $ISENT$ and $CMSI$ are investor sentiment and managerial sentiment indicators, respectively, Γ_0 is the intercept, Γ_1^+ applies when $\Delta ISENT_{t-p} \geq 0$, Γ_1^- applies when $\Delta ISENT_{t-p} < 0$, Γ_2^+ applies when $\Delta CMSI_{t-p} \geq 0$, Γ_2^- applies when $\Delta CMSI_{t-p} < 0$, similarly for Φ_1^+ and Φ_1^- in the case of error correction term ECT_{t-1}, I_t is the Heaviside step function and is specified as in Equation 8, ν_t is the error term and p is the lag length.

In Table 3.9 error correction term (ECT) for positive shocks is statistically significant suggesting that investor sentiment reacts to disequilibrium in the short-run. The results also show interesting dynamics between managerial and investor sentiments. In a lag of 4 months, positive managerial sentiment is a negative predictor of investor sentiment. However, as in Table 3.5 and 3.6, we show that managerial sentiment has a positive association with investor sentiment at both time *t* and *t-1*. The results imply that managerial sentiment is transmitted positively to investor sentiment in a very shorter period, however, as time passes and more information that disconfirms previous managerial beliefs becomes available, investor sentiment begins to respond negatively. Furthermore, the length of the lag in which investor sentiment begins to react negatively, i.e. 4 months, is very reasonable in our case. Surveys on managerial sentiment we used to construct CMSI usually request managers' expectations on the development of their business activities in three months' window. Therefore, as managers are over-confident in their estimation, we expect higher positive managerial sentiment around time *t*. For 3-month periods, business results appear below managers' previous estimations and hence, low level of investor sentiment.

Table 3.9
Results of the asymmetric sentiment transmission from managers to investors

ISENT is the investor sentiment index and CMSI is the core managerial sentiment index. The identification of the Heaviside indicator function is provided in Equation 8. Lag length for explanatory variable is determined using Akaike information criterion (AIC).

	Dependent Variable: Investor Sentiments (ΔISENT$_t$)			
	Estimate	St. Error	t-stat	p-value
(Intercept)	0.145	0.174	0.832	0.406
$\Delta CMSI^{+}_{t-1}$	-0.016	0.028	-0.562	0.575
$\Delta CMSI^{+}_{t-2}$	0.038	0.027	1.408	0.161
$\Delta CMSI^{+}_{t-3}$	0.025	0.027	0.912	0.363
$\Delta CMSI^{+}_{t-4}$	-0.052	0.027	-1.918	0.057*
$\Delta CMSI^{-}_{t-1}$	0.026	0.026	1.012	0.313
$\Delta CMSI^{-}_{t-2}$	0.001	0.024	0.028	0.978
$\Delta CMSI^{-}_{t-3}$	0.031	0.024	1.284	0.201
$\Delta CMSI^{-}_{t-4}$	0.012	0.025	0.487	0.627
$\Delta SENT^{+}_{t-1}$	-0.479	0.169	-2.843	0.005***
$\Delta SENT^{+}_{t-2}$	-0.13	0.169	-0.77	0.443
$\Delta SENT^{+}_{t-3}$	-0.146	0.162	-0.9	0.369
$\Delta SENT^{+}_{t-4}$	0.352	0.153	2.296	0.023**
$\Delta SENT^{-}_{t-1}$	0.017	0.153	0.113	0.91
$\Delta SENT^{-}_{t-2}$	-0.245	0.133	-1.836	0.068*
$\Delta SENT^{-}_{t-3}$	0.032	0.137	0.233	0.816
$\Delta SENT^{-}_{t-4}$	-0.121	0.133	-0.913	0.363
ECT^{+}_{t-1}	-0.125	0.062	-2.023	0.045**
ECT^{-}_{t-1}	0.135	0.133	1.016	0.311

Level of significance for correlation coefficients are ***:0.01, **:0.05, *:0.1.

3.7. Conclusion

The chapter examined the relationship between managerial sentiment and investor sentiment in the UK market. To measure managerial sentiment, we constructed a core managerial sentiment index (CMSI) based on Salhin et al. (2016) findings. Comparing the performance of investor sentiment measures (NIPO, CEFD and VFTSEIX) to managerial sentiment index, we provided evidence that managerial sentiment is a powerful predictor of stock market returns and its performance is less sensitive to changes in return indices compared to individual measures of investor sentiment. We further estimated the impact of investor sentiment on managerial sentiment by employing a VARX model. Results showed that managerial sentiment positively forecasts changes in investor sentiment in shorter periods.

Moreover, our preliminary cointegration tests indicated a long-run relationship between investor sentiment (ISENT) and managerial sentiment (CMSI). To further investigate their long-run relationship, we extended our cointegration tests to allow for the estimation of asymmetric relationship between ISENT and CMSI. Our findings suggest that investor sentiment responds to positive rather than negative shocks in managerial sentiment. These results indicate that investor sentiment converges to the long-run equilibrium relationship when managers possess positive sentiment towards prospects of their businesses. In addition, we used ATVECM to provide an evidence on the overconfidence of managers and how it leads to negative investor sentiment with a lag of four months.

Our study has several important implications. Firstly, it provides investors with evidence on the importance of managerial sentiment as a powerful predictor of stock market returns. Managers, despite their over-confidence, have superior information; therefore, their sentiment is well informed of fundamental changes compared to investors. Secondly, our results are important for regulators who are concerned with the relationship between managers and investors. The findings we provided on long and short-run dynamics in the relationship between managers and investors reveals unobserved behaviour of managers in influencing investors decisions and actions. The results might provide more information on role that managers play in the formation of pricing bubble. Future research on this area could be directed to understand the feedback in the relationship from investor to managerial sentiment. Such research would provide more insights on how managers views on their businesses are affected by the prevailing market/investor sentiment.

Appendix 1: Construction of the Core Managerial Sentiment Indicator (CMSI)

We construct the index from a linear combination of selected survey questions that show significant prediction of sector returns as documented by Salhin et al. (2016). The selected questions are reported in Table 3.10.

Table 3.10
Survey questions for constructing the Core Managerial Sentiment Index

The table reports managerial survey questions that show significant power in predicting sector returns as reported by Salhin et al. (2016).

Sector	Questions
Manufacturing	• Expectations about the future level of production. • Assessment of the current order-book levels.
Construction	• Evolution of current overall order book. • Employment expectation in the next 3 months of the business activity.
Retail Trade	• Order expectation in the next 3 months of the business activity.
Services	• Business situation development over the past three month of the business activity. • Evolution of demand over the past three month of the business activity. • Employment expectation in the next 3 months of the business activity

Score for every sector is the simple arithmetic mean of the selected questions as follow:

$$CMSI_s = \frac{\sum_{i=1}^{n} Quest_i}{ns}$$

where, $CMSI_s$ is the core managerial sentiment indicator for sector s, $Quest_i$ is the selected question i for sector s, n is the number of selected questions for sector s.

The aggregate market CMSI is the weighted average of each sector CMSI as follow:

$$CMSI = \sum_{s=1}^{4} W_s \, CMSI_s$$

where $CMSI$ is the core managerial sentiment indicator for the UK market, W_s is the weight for sector s, $CMSI_s$ is the core managerial sentiment indicator for sector s.

We calculated sector weights following the same methodology by Salhin et al. (2016) with 50% assigned to Manufacturing, 37.5% to Services, and 6.25% for each of the Retail Trade and Construction indicators. In addition, the CMSI is scaled to have a mean of 100 and a standard deviation of 10.

Appendix 2: Construction of the Investor Sentiment Index (ISENT)

We follow Baker & Wurgler (2006) procedures to construct a composite index of investor sentiment (ISENT) using three individual measures of investor sentiment; the number of initial public offerings (NIPOs), closed-end funds discounts (CEFD), and volatility index (VFTSEIX). Firstly, we estimated the first principal component of the three standardised measures of investor sentiment and their lags. This results in a first-phase index with six loadings one for each of the current values of our measures and their lags. We then calculate the correlation coefficient between the first-phase index and each of the current values of the three measures and their lags. We then selected between variables and their lags for the second stage PCA based on whichever has higher correlation with the first-phase index. This results in a composite index of investor sentiment (ISENT) as follow:

$$ISENT_t = 0.513\, NIPO_{t-1} - 0.554\, CEFD_t - 0.655\, VFTSEIX_{t-1},$$

The first component of the PCA results for ISENT explains 62% of the common variation. The correlation between the first-phase index and ISENT is 0.70. Furthermore, to account for the possibility that the PCA captures the common business cycle component instead of investor sentiment, we followed the same steps as before to compute an orthognalised version of ISENT as follow:[7]

$$ISENT_t^{\perp} = 0.590\, NIPO_t - 0.448\, CEFD_t - 0.671\, VFTSEIX_{t-1},$$

[7] The index is orthognalised against Term-spread, yield on 10 year governmental bonds, growth rate in GDP, inflation, unemployment rate and percentage change in the level of industrial production.

The first component of the PCA results for ISENT explains 55% of the common variation. The correlation between the $ISENT_t$ and $ISENT_t^{\perp}$ is 0.67. Similar to Baker & Wurgler (2006), we found no impact on the properties of ISENT after orthognalising against macro factors.

Chapter 4

Managerial Sentiment, Asset Prices and Risk Premiums

4.1. Introduction

Efforts to explain stock market returns reveal that one model does not fit all. Early attempts by Lintner (1965); Sharpe (1964); Treynor (1961) gave rise to the Capital Asset Pricing Model in which stock returns are priced using the excess of market returns over the risk free rate or market risk premium. However, empirical evidence shows that this one factor model lacks the ability to explain the cross-sectional variation in stock returns (e.g. Banz (1981); Bhandari (1988); Chan (1985); Gibbons (1982); Hyde & Sherif (2010); Reinganum (1981)). The univariate model was enhanced by Fama & French (1993) who propose the addition of size and value premiums to the CAPM estimation. The inclusion of the difference between returns on small and big stocks and between high and low book-to-market stocks increases the explanatory power of models of the cross-sectional variation of returns. Nevertheless, subsequent research on the Fama & French (1993) three factor model shows that only a small portion of the variation of stock returns is explained (He et al., 1996). In addition, the three factor approach fails to explain the existence of stock market anomalies such as the winner-loser effect of

Jegadeesh & Titman (1993) which is subsequently captured by the momentum factor developed by Carhart (1997).

The classical framework of asset pricing models has been further frustrated by the failure to explain consistent deviation of stock prices from their fundamental values. One example is the closed-end funds discount puzzle. Closed-end fund share prices should approximately equal the fund's net asset value per share (NAV). However, closed-end funds usually trade at prices below the NAV. Lee et al. (1991) argue that closed-end fund discount is evidence of the impact of investor sentiment on stock returns. In addition, studies of investor irrationality indicate a role for investor sentiment in explaining time-series and cross-sectional variation of stock market returns. Examples of these studies are (Abraham et al. (1993); Baker & Wurgler (2006); Kothari & Shanken (1997); Neal & Wheatley (1998); Shiller (1981, 2000); Wang (2003)).

The impact of managerial sentiment on stock returns has already been established in previous research. Salhin et al. (2016) show that managerial sentiment is a reliable predictor of time series of stock returns. In addition, a number of studies show that managers use pro forma earnings disclosures along with other corporate actions to cater for investor sentiment, and hence returns (see, e.g., Baker et al. (2003); Brown et al. (2012); Cooper et al. (2001)). Furthermore, Baker & Wurgler (2013) provide detailed discussion on how managers react to investor sentiment and asset mispricing through market timing. However, relatively little consideration has been paid to the importance of managerial sentiment in explaining the cross-sectional variation of stock market returns. The present study seeks to address that gap in the literature by testing the performance of a set of asset pricing models that incorporate managerial sentiment. Similar to investor sentiment, we expect that managerial sentiment can explain the variation in cross-sectional stock returns.

In this chapter, we test alternative models of asset pricing such as CAPM, Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF) to compare their results with managerial and investor sentiment-augmented asset pricing models. Similar to chapter 2, we construct our core managerial sentiment index (CMSI) using business surveys provided by the European Commission (EC). For investor sentiment, we employ principal component analysis to extract the common sentiment component of three measures of investor sentiment; closed-end fund discount, the number of initial public offering and volatility index which we call (ISENT).[1] We examine the models against four test portfolios formed on size, book-to-market, standard deviation, and intersecting portfolios ranked on size and momentum factors.[2] Our findings show that managerial sentiment is able to explain 75% (3 out of four) of value-weighted test portfolios compared to CAPM (25%), FF(25%), 4FF(25%) and 4FF plus ISENT (50%). In addition, Hansen and Jagannathan model misspecification test suggests that models that incorporate the CMSI yields smaller mispricing error relative to CAPM, FF and 4FF.

Moreover, Baker & Wurgler (2013) argue that estimating the impact of investor and managerial sentiment simultaneously would be expected to provide more insight on the relationship with stock returns. Therefore, we test models that include proxies for both investor and managerial sentiment in addition to the four factors of Carhart (1997). Our results demonstrate that such models can explain 100% of equally and value-weighted test portfolios. Furthermore, we follow Lemmon & Portniaguina (2006) and examine the impact of sentiment indices on size, value and momentum premiums. Similar to their findings on investor sentiment, we show that lagged measures of managerial sentiment negatively forecast short-term changes (1-3 month) in size premium. In addition, we find that the value premium responds to relatively long-term changes (12 month) in investor and managerial sentiment indices. However, and consistent with Lemmon & Portniaguina (2006), we fail to find evidence on the impact of investor or managerial sentiment on momentum premium.

[1] More details on the power of these measures to predict stock returns are provided by Baker & Wurgler (2006, 2007); Lee et al. (1991); Whaley (2000), and Nikkinen & Vähämaa (2010)).

[2] Size, book-to-market, and momentum factors and test portfolios are obtained from the Xfi Centre for Finance and Investment at the University of Exeter which updates the sample of Gregory et al. (2013). Available at http://business-school.exeter.ac.uk/research/centres/xfi, accessed on 18 February 2017.

We structure the rest of this chapter is as follow: Section 2 presents the empirical model and methodology employed to test alternative asset pricing models. Section 3 discusses data and provide some summary statistics. In section 4, we test different fundamental and behavioural asset pricing models. Section 5, we investigate the impact of sentiment indices on size, value and momentum premiums. Section 6 concludes.

4.2. Empirical models, specification tests and variable constructions

4.2.1 Empirical models

We base the first part of our analysis on six asset pricing models with different specifications incorporating behavioural as well as fundamental factors.

4.2.1.1 Capital Asset Pricing Model (CAPM)

$$R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \varepsilon_{pt}, \tag{4.1}$$

where R_{pt} is the return of portfolio p for month t, R_{ft} is the risk-free rate for month t, $RMRF_t$ is the standard CAPM market risk factor calculated as $R_{mt} - R_{ft}$, where R_{mt} is the return on market portfolio and ε_{pt} is the error term.

4.2.1.2 Fama-French (1993) three factor model (FF)

$$R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \beta_{p,SMB}\, SMB_t + \beta_{p,HML}\, HML_t + \varepsilon_{pt}, \tag{4.2}$$

where SMB_t denotes the size factor and HML_t is the value factor for time t. SMB and HML are calculated from six portfolios (2 size and 3 book-to-market (BTM) portfolios).

4.2.1.3 Carhart (1997) four factor model (4FF)

In addition to the three factors of Fama & French (1993), Carhart (1997) added a momentum term to represent "winner minus loser" factor as follow:

$$\begin{aligned} R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \beta_{p,SMB}\, SMB_t + \beta_{p,HML}\, HML_t \\ + \beta_{p,MOM}\, MOM_t + \varepsilon_{pt}, \end{aligned} \tag{4.3}$$

where MOM_t is the momentum factor at month t.

4.2.1.4 Four factor model plus managerial sentiment (4FF_CMSI)

$$\begin{aligned} R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \beta_{p,SMB}\, SMB_t + \beta_{p,HML}\, HML_t \\ + \beta_{p,MOM}\, MOM_t + \beta_{p,CMSI}\, CMSI_t + \varepsilon_{pt}, \end{aligned} \tag{4.4}$$

where $CMSI_t$ is the core managerial sentiment index at month t.

4.2.1.5 Four factor model plus investor sentiment (4FF_ISENT)

$$\begin{aligned} R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \beta_{p,SMB}\, SMB_t + \beta_{p,HML}\, HML_t \\ + \beta_{p,MOM}\, MOM_t + \beta_{p,ISENT}\, ISENT_t + \varepsilon_{pt}, \end{aligned} \tag{4.5}$$

where $ISENT_t$ is a composite index of investor sentiment at month t.

4.2.1.6 Four factor model plus investor & managerial sentiment (4FF_ISENT_CMSI)

$$R_{pt} - R_{ft} = \alpha_p + \beta_{p,RMRF}\, RMRF_t + \beta_{p,SMB}\, SMB_t + \beta_{p,HML}\, HML_t + \beta_{p,MOM}\, MOM_t + \beta_{p,ISENT}\, ISENT_t + \beta_{p,CMSI}\, CMSI_t + \varepsilon_{pt}, \tag{4.6}$$

In addition to the previous models, we employed forecasting regressions with different horizons to test if investor and managerial sentiment predict time-series variation in value, size and momentum premium. Following Lemmon & Portniaguina (2006) and Swaminathan (1996), we regress size (SMB), value (HML) and momentum (MOM) factors on lagged values of CMSI and ISENT as well as control variables. Control variables include; lagged risk factors, 3-Month Treasury bill (T-bill), T-spread calculated as the difference in yields between 10-Year and 3-Month T-bill, percentage change in industrial production level (IPT) and GDP growth rate. We estimate OLS models for one, three, six and twelve month horizons as follow:

$$Factor_t = \phi_0 + \phi_1\, Factor_{t-i} + \phi_2\, CMSI_{t-i} + \sum_{j=0}^{5} \beta_j \psi_{jt-i} + \upsilon_t, \tag{4.7}$$

$$Factor_t = \phi_0 + \phi_1\, Factor_{t-i} + \phi_2\, ISENT_{t-i} + \sum_{j=0}^{5} \beta_j \psi_{jt-i} + \upsilon_t, \tag{4.8}$$

where $Factor_t$ is either the size (SMB), value (HML) and momentum (MOM) premiums at month t, $Factor_{t-i}$ is the lagged values of risk premiums, $CMSI_{t-i}$ is the core managerial sentiment index, $ISENT_{t-i}$ is a composite index of investor sentiment, i denotes the forecasting horizon with values one, three, six and twelve month, ψ_{jt-i} is a matrix includes control variables, ϕ_0 is an intercept and υ_t is the disturbance term. We use Newey-West standard errors to assess the statistical significant of regression coefficients.

4.2.2 Specification tests

To test the six asset pricing models in section 2.1., we rely on both parametric and non-parametric tests.

4.2.2.1 Parametric tests

For parametric tests, we follow Fama & French (2016) by using Gibbons et al. (1989) test statistic [hereafter GRS]. Since each asset pricing model yields a vector of intercepts $\widehat{\alpha}_p = [\widehat{\alpha}_{p1}, \widehat{\alpha}_{p2}, \widehat{\alpha}_{p3}, \ldots\ldots \widehat{\alpha}_{pn}]$ where n is the number of test portfolios, the GRS test examines if all alphas are jointly indistinguishable from zero. The test has been used widely in asset pricing literature (Michou et al. (2007); Chou et al. (2012); Gregory et al. (2013); and Nichol & Dowling (2014)).[3]

4.2.2.2 Non-parametric test

Parametric tests provide evidence on whether a specific model, given a set of assumptions about the distribution of the underlying data, provides an accurate estimation of the observed data. To confirm robustness of our parametric tests, we also compare models using the non-parametric Hansen & Jagannathan (1997) distance (HJ distance, hereafter). Our choice of the method is consistent with previous studies on empirical tests of asset asset pricing models (Chen & Sherif, 2016; Gospodinov et al., 2016; Kan & Robotti, 2009). The HJ distance measures the distance between the family of stochastic discount factors (SDF) in which all

[3] The GRS test is criticised for producing less robust results since it assumes the residuals from the model to be uncorrelated, normally distributed and homoscedastic (Cochrane, 2000). Therefore, we address such criticism by estimating our models using systematic GMM and test the hypothesis that all alphas are jointly different from zero using Wald test. However, there is no significant difference in the results. The GMM findings are available from authors upon request.

assets are correctly priced and the SDF associated with a candidate asset pricing model. Hansen & Jagannathan (1997) define the distance as follow:

If an asset pricing model is correctly specified, there must be a pricing kernel $m \ \in M$ that correctly price an asset as in Euler's equation E(mR) = p, where R is the asset payoffs and p is the asset price, and M is a family of all pricing kernels that correctly price every asset. If an asset pricing model is false, its pricing kernel proxy $\omega \ \notin M$. Therefore, there will be a positive distance between ω and m as follow:

$$\delta = \min_{m \ \in L^2} \|\omega - m\| \,, \tag{4.9}$$

Equation 4.9 can be then rewritten as a Lagrangian minimization problem as follow:

$$\delta^2 = \underset{m \in L^2}{min} \ \underset{\lambda \in R^n}{sup} \ \{E(\omega - m)^2 + 2\acute{\lambda} \ [E(mR) - p]\}, \tag{4.10}$$

Since m can be practically estimated by $\tilde{m}$, it can be used along with $\widetilde{\lambda}$ to solve equation 4.10. Solving equation 4.10 results in:

$$\omega - \ \tilde{m} = \ \widetilde{\lambda}^{\prime} R, \tag{4.11}$$

where $\omega - \ \tilde{m}$ is the minimal adjustment to ω in order to make it a correct pricing kernel and

$$\widetilde{\lambda} = E(R\acute{R})^{-1} \ E(\omega R - p), \tag{4.12}$$

Hansen and Jagannathan show that the distance equals (δ):

$$\delta = \ \|\omega - \widetilde{m}\| = \left\|\widetilde{\lambda}^{\prime} R\right\| = \left[\acute{\widetilde{\lambda}} \ E(R\acute{R})\widetilde{\lambda}\right]^{1/2}, \tag{4.13}$$

Substituting the value of $\widetilde{\lambda}$ from equation 4.12 gives:

$$\delta = \left[E(\omega R - p)' \; E(R R')^{-1} \; E(\omega R - p)\right]^{1/2}, \tag{4.14}$$

4.2.3 Variables constructions

Since investor and managerial sentiment are unobservable, we extract from business surveys and stock market measurements. In this section, we describe the procedures we follow to construct those proxies for investor and managerial sentiment.

4.2.3.1 Investor Sentiment

We use principal component analysis to construct a composite measure of investor sentiment (ISENT) using three indicators; the number of initial public offerings (NIPOs), closed-end fund discounts (CEFD), and volatility index (VFTSEIX). We follow the same procedure described by Baker & Wurgler (2006) to construct the index. In the first phase, we estimate the first principal component of three distinct proxies for investor sentiment and their lag values which results in an index with six loadings one for each of the current and lag values of the proxies as follow:

$$Comp_{1,1} = \Theta_{1,1}^{T}[\mathcal{X}|\ \mathcal{L}], Comp_{1,1} \in \mathbb{R} \tag{4.15}$$

where $COMP_{1,1}$ is the first component of investor sentiment measures from the first-phase PCA, Θ is a vector of coefficients of the first component and "$\mathcal{X}|\ \mathcal{L}$" augments $\overrightarrow{\mathcal{X}}$ and $\overrightarrow{\mathcal{L}}$ that contain the current values of the three measures of investor sentiment as x_1, x_2, and x_3 and lagged values ℓ_1, ℓ_2, and ℓ_3, respectively as follow:

$$\overrightarrow{\mathcal{X}} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}, \overrightarrow{\mathcal{L}} = \begin{pmatrix} \ell_1 \\ \ell_2 \\ \ell_3 \end{pmatrix}, \quad (16)$$

we select $\overrightarrow{\mathcal{Z}}$ such that:

$$\forall i \in \{1, 2, 3\}, \ \overrightarrow{\mathcal{Z}}_i = \begin{cases} x_i, & \rho(x_\iota, \ \ell_\iota) > \ \rho(x_\iota, \ \ell_\iota) \\ x_i \bigoplus \ell_i, & \rho(x_\iota, \ \ell_\iota) = \ \rho(x_\iota, \ \ell_\iota) \\ \ell_i, & \rho(x_\iota, \ \ell_\iota) < \ \rho(x_\iota, \ \ell_\iota) \end{cases} \quad (4.16)$$

where ρ is the correlation coefficient and $\rho : \mathbb{R}^2 \to \mathbb{R}$ and $\overrightarrow{\mathcal{Z}}$ contain investor sentiment measures for the second phase index.

More plainly, we calculate the correlation between the first-phase index and each of the current and lagged values of the three proxies. We select between variables and their lags to implement a second phase PCA based on whichever has higher correlation coefficient with the first-phase index. The second-phase index is then defined as:

$$COMP_{1,2} = \Theta_{1,2}^T \overrightarrow{z}, \quad (4.17)$$

where $COMP_{1,2}$ is the first component of investor sentiment from the second-phase PCA which is translated to an index of investor sentiment ($ISENT_t$) as follow:

$$ISENT_t = 0.513 \, NIPO_{t-1} - 0.554 \, CEFD_t - 0.655 \, VFTSEIX_{t-1}, \quad (4.18)$$

The PCA first component for ISENT explains 62% of the common variance. The correlation coefficient between ISENT and the first-step index is 0.70.

4.2.3.2 Managerial Sentiment

Similar to chapter 3, we construct a core managerial sentiment index (CMSI) from a linear combination of specific managerial survey questions which show significant power in predicting sector returns as reported by Salhin et al. (2016). The survey questions used in calculating CMSI are reported in Table 4.1.

Table 4.1
Survey questions for constructing the Core Managerial Sentiment Index

The table reports managerial survey questions that show significant power in predicting sector returns as reported by Salhin et al. (2016).

Sector	Questions
Manufacturing	• Expectations about the future level of production. • Assessment of the current order-book levels.
Construction	• Evolution of current overall order book. • Employment expectation in the next 3 months of the business activity.
Retail Trade	• Order expectation in the next 3 months of the business activity.
Services	• Business situation development over the past three month of the business activity. • Evolution of demand over the past three month of the business activity. • Employment expectation in the next 3 months of the business activity

CMSI for every sector is calculated as the simple arithmetic mean of the survey questions as follow:

$$CMSI_i = \frac{\sum_{q=1}^{n} Quest_q}{ns}, \tag{4.19}$$

where, $CMSI_i$ is the core managerial sentiment index for sector i, $Quest_q$ is the survey question q for sector i, n is the number of survey questions for sector i.

The market CMSI is the weighted average of the CMSI per each sector as follow:

$$CMSI = \sum_{i=1}^{4} W_i \, CMSI_i, \tag{4.20}$$

where $CMSI$ is the core managerial sentiment index for the UK market, W_i is the weight for sector i, $CMSI_i$ is the core managerial sentiment index for sector i.

Sector weights are calculated following the procedures described by Salhin et al. (2016) with 50% to Manufacturing, 37.5% to Services, and 6.25% for each of the Retail Trade and Construction sectors. The CMSI is scaled to have a mean of 100 and a standard deviation of 10.

4.3. Data

To examine our models, we use UK data on risk factors, investor and managerial sentiment, test portfolios and macroeconomic variables. Data covers the period from January 2000 to September 2014.

4.3.1 Data on risk factors

We obtain data on market (RMRF), size (SMB), value (HML), and Momentum (MOM) risk premium for the period from January 2000 to September 2014.

Market risk premium is the difference between return on the market portfolio (FTSE All Share Index) and the risk-free rate (three-month T-Bill). SMB and HML are calculated using six portfolios formed from the intersection of two size portfolios [Small (S) and Big (B)], and three value portfolios [High (H), Medium (M), and Low (L)]. Size is measured by market capitalization and value is measured by the book-to-market ratio (BTM). The calculation of SMB and HML is as follow:

$$SMB = \frac{\mathrm{SL + SM + SH}}{3} - \frac{\mathrm{BL + BM + BH}}{3}, \tag{4.21}$$

$$HML = \frac{\mathrm{SH + BH}}{2} - \frac{\mathrm{SL + BL}}{2}, \tag{4.22}$$

Momentum (MOM) factor is calculated from six portfolios formed using the intersection of size [Small (S) and Big (B)] and past stock return performance or momentum [Up (U), Medium (M) and Down (D)]. The MOM factor is then calculated as follow:

$$MOM = \frac{\mathrm{SU + BU}}{2} - \frac{\mathrm{SD + BD}}{2}, \tag{4.23}$$

Data on RMRF, SMB, HML, and MOM factors are obtained from the Xfi Centre for Finance and Investment at the University of Exeter which updates the sample in Gregory et al. (2013).

4.3.2 Data on investor sentiment

To construct a composite measure of investor sentiment, we use data on the number of initial public offerings (NIPOs), closed-end fund discount (CEFD), and FTSE 100 Volatility Index (VFTSEIX) as measures of investor sentiment. The number of initial public offerings (NIPOs) is obtained from London Stock Exchange for the period from January 2000 to September 2014. Total number of IPOs equal 2054 companies for the entire sample period. For closed-end fund discount (CEFD), we follow Lee et al. (1991) to calculate a monthly value-weighted index of discounts as follow:

$$CEFD_t = \left[\sum_{i=1}^{n_t} \frac{NAV_{it} - P_{it}}{\sum_{i=1}^{n_t} NAV_{it}} \right] X\ 100, \tag{4.24}$$

where NAV_{it} is the net asset value of closed-end fund i at the end of month t, P_{it} is the share price of closed-end fund i at the end of month t, and n_t is the number of closed-end funds with available price *(P)* and net asset value *(NAV)* at the end of month *t.* Data on NAV and P are obtained from Datastream.

The Volatility Index (VFTSEIX) is the implied standard deviation of options on the FTSE100 Index. VFTSEIX reflects how certain investors are about the volatility of the stock market while higher (lower) VFTSEIX refers to pessimistic (optimistic) investors. VFTSEIX is obtained from Datastream.

4.3.3 Data on managerial sentiment

To construct our core managerial sentiment index (CMSI), we use monthly business surveys provided by the European Commission (EC). Survey data covers the period from January 2000 till September 2014 for four UK sectors, namely; Manufacturing, Construction, Retail Trade, and Services. Based on Salhin et al. (2016) findings, we select survey questions that have strong predictive power of stock returns in order to construct CMSI. Details on the construction of the CMSI is provided in section 3.

4.3.4 Test portfolios

We use four sets of equally-weighted (EW) and value-weighted (VW) test portfolios formed on value, size, standard deviation and momentum. The first set contains 10 portfolios formed on deciles of book to market ratio of all UK firms. The second set is constructed from 10 portfolios formed on deciles of size of all UK firms. The third set contain 25 (5 x 5) portfolios ranked on the standard deviation of prior 12-month returns. The fourth set includes 25 (5 x 5) intersecting size and momentum portfolios formed by using the whole sample of firms. Size portfolios are formed from four portfolios from the largest 350 UK firms and one from the rest of the whole sample. Momentum portfolios are formed using the whole sample of UK firms. Similar to risk factors, data on test portfolios are obtained from the Xfi Centre for Finance and Investment.[4]

4.3.5 Macroeconomic variables

We use macroeconomic series as control variables to test the impact of sentiment indices on size, value and momentum premiums. We obtain monthly data on three-month treasury bill (T-bill), unemployment (UNEMP), Term spread (calculated as the yield on 10 years' government bonds minus three-month T-bill rate), percentage change in total index of production (IPT), and GDP growth rate (GDP). Data is obtained from Datastream for the period from January 2000 to September 2014. GDP is only available in quarterly form; therefore, we employ polynomial interpolation to convert GDP figures into monthly values. Descriptive statistics on factors, sentiment measures, test portfolios and control variables are provided in Tables [4.2-4.7].

4.4. Testing fundamental and behavioural asset pricing models

Time series regressions for asset pricing models are reported in Tables 8-11. In each table, we report estimates of the intercept term and their statistical significance for each asset pricing model and test portfolios. We only report estimates of the intercept term since our main objective is to test for the rejection of the null hypothesis that all α values are indistinguishable from zero using GRS test

[4] More details are available at http://business-school.exeter.ac.uk/research/centres/xfi, accessed on 18 February 2017. Construction of factors and test portfolios is detailed in Gregory et al. (2013).

Table 4.2
Descriptive statistics for sentiment indicators, Fama-French and Carhart factors and macroeconomic indices.

Data covers the period from January 2000 to September 2014 for the UK market. ISENT is a proxy for investor sentiment and calculated using principal component analysis (PCA) of three measures of investor sentiment; the number of initial public offerings, closed-end fund discounts and FTSE100 volatility index. CMSI is a proxy for managerial sentiment. RMRF is the market risk premium, SMB is the size risk premium, HML is the value risk premium and MOM reflects the momentum effect. T-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT and GDP are percentage change in industrial production level and the GDP growth rate, respectively.

Panel A: Risk Factors

	mean (%)	sd (%)	median (%)	trimmed (%)	min (%)	max (%)
RMRF	0.22	4.16	0.85	0.45	-13.61	9.90
SMB	0.23	3.45	0.15	0.31	-11.48	15.61
HML	0.50	3.55	0.38	0.32	-18.61	12.29
MOM	0.79	5.54	1.10	1.19	-25.03	16.04

Panel B: Sentiment

	mean	sd	median	trimmed	min	max
ISENT	0.00	1.37	0.04	0.04	-3.84	3.10
CMSI	95.45	12.03	98.00	96.86	55.10	111.8

Panel C: Macroeconomic Indices

	mean	sd	median	trimmed	min	max
T-bill	2.95	2.14	3.82	2.94	0.23	5.96
T-spread	1.09	1.31	0.93	1.03	-0.71	3.60
UNEMP	3.49	0.83	3.10	3.44	2.40	4.90
IPT	-0.07	0.98	0.00	-0.03	-4.68	2.60
GDP	0.43	0.66	0.56	0.53	-2.2	1.42

statistic. In addition, we report the mean adjusted R^2 of test portfolios for each model. Estimates and test statistics are reported for both equally-weighted (Panel A) and value-weighted portfolios (Panel B).

For value portfolios, traditional CAPM fails the GRS with 70% of EW and 30% of VW test portfolios have significant intercepts. Insignificant intercepts for CAPM are more apparent in low value portfolios. Results for Fama-French three factor model are not notably different from CAPM with the exception of the GRS test for VW portfolios. FF intercepts are 60% significant for EW portfolios

Table 4.3

Correlation for sentiment, Fama-French and Carhart factors and macroeconomic indices.

Data covers the period from January 2000 to September 2014 for the UK market. ISENT is a proxy for investor sentiment and calculated using principal component analysis (PCA) of three measures of investor sentiment; the number of initial public offerings, closed-end fund discounts and FTSE100 volatility index. CMSI is a proxy for managerial sentiment. RMRF is the market risk premium, SMB is the size risk premium, HML is the value risk premium and MOM reflects the momentum effect. T-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT and GDP are percentage change in industrial production level and the GDP growth rate, respectively.

	ISENT	CMSI	RMRF	SMB	HML	MOM	T-bill	T-spread	UNEMP	IPT
CMSI	0.69***									
RMRF	-0.03	-0.09								
SMB	-0.03	-0.09	0.17*							
HML	0.04	0.13	0.17*	-0.12						
MOM	0.15*	0.15*	-0.27***	-0.11	-0.48***					
T-bill	0.30***	0.59***	-0.16*	-0.12	0.14	0.05				
T-spread	-0.42***	-0.63***	0.13	0.10	-0.11	-0.05	-0.92***			
UNEMP	-0.40***	-0.70***	0.16*	0.11	-0.05	-0.10	-0.82***	0.76***		
IPT	0.12	0.09	0.18*	0.09	0.05	0.02	0.00	-0.01	0.02	
GDP	0.43***	0.49***	0.17*	0.15	0.19*	0.03	0.14	-0.15*	-0.13	0.26***

Table 4.4

Descriptive statistics for the 10 Book-to-Market (BTM) portfolios.

The table reports descriptive statistics for 10 portfolios formed on deciles of book to market ratio of all UK firms. Data covers the period from January 2000 to September 2014. Equally and value-weighted portfolio are formed using the whole available sample of UK firms. V1 denotes the portfolio with the lowest book-to-market ratio and V10 denotes the portfolio with the highest book-to-market ratio.

Panel A: Equally-weighted

	V1	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	*V10*
mean	0.21	0.54	0.97	0.80	1.18	1.07	1.11	1.12	1.29	1.71
sd	6.08	5.31	5.07	5.08	5.42	5.03	5.54	5.72	5.81	7.27
median	1.09	1.07	1.53	0.96	1.48	0.96	1.49	1.34	1.50	0.80
trimmed	0.55	0.95	1.29	0.99	1.35	1.20	1.38	1.27	1.31	1.27
min	-24.59	-22.02	-19.13	-21.06	-20.09	-19.19	-21.54	-23.75	-21.9	-22.47
max	20.67	17.21	18.56	21.77	31.46	24.69	28.4	30.56	32.63	50.76

Panel B: Value-weighted

	V1	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	*V10*
mean	0.26	0.59	0.64	0.83	0.82	0.89	0.86	0.81	0.87	1.29
sd	3.86	3.67	4.58	5.06	5.80	5.44	5.51	5.16	6.43	8.16
median	0.46	0.96	1.27	1.09	1.63	1.23	1.37	1.42	1.25	1.53
trimmed	0.44	0.77	1.01	1.08	1.23	1.04	1.07	1.13	0.94	1.29
min	-12.29	-10.77	-22.55	-18.14	-21.34	-23.63	-16.4	-18.65	-23.69	-29.61
max	10.93	9.01	9.41	12.77	14.37	20.05	14.48	14.62	24.19	26.52

Table 4.5
Descriptive statistics for the 10 size portfolios.

The table reports descriptive statistics for 10 portfolios formed on deciles of size of all UK firms. Data covers the period from January 2000 to September 2014. Equally and value-weighted portfolio are formed using the whole available sample of UK firms. S1 denotes the portfolio with the smallest firm size and S10 denotes the portfolio with the largest firm size.

Panel A: Equally-weighted

	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*
mean	1.32	1.18	1.04	1.2	0.94	1.08	0.86	0.8	0.79	0.7
sd	5.5	5.94	5.74	6.05	5.86	5.99	6.14	5.8	5.63	4.35
median	1.14	1.18	1.68	1.13	1.3	1.44	0.85	1.11	1.56	1.18
trimmed	1.05	1.18	1.2	1.18	0.99	1.15	0.98	1.09	1.08	0.97
min	-13.26	-22.32	-22.48	-23.04	-19.6	-18.14	-24.86	-25.9	-19.59	-15.35
max	24.07	37.14	30.16	40.05	30.61	33.73	30.91	24.72	18.09	10.8

Panel B: Value-weighted

	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*
mean	0.58	1.1	1.05	1.13	0.96	0.97	0.89	0.79	0.83	0.49
sd	5.24	5.5	5.41	5.91	5.64	5.46	5.65	5.51	5.23	3.84
median	0.77	1.09	1.57	1.18	1.26	1.28	1.01	1.2	1.56	0.93
trimmed	0.5	1.09	1.23	1.17	1.05	1.12	1.03	1.1	1.12	0.66
min	-14.79	-21.21	-22.67	-22.83	-19.35	-17.59	-24.19	-26	-19.39	-13.98
max	23.7	25.26	25.09	26.94	23.16	21.25	24.07	19.53	13.9	8.42

Table 4.6

Descriptive statistics for 25 standard deviation portfolios.

The table reports descriptive statistics for 25 portfolios formed on prior 12-month standard deviation of all UK firms stock returns. Equally and value-weighted portfolio are formed using the whole sample of UK firms from January 2000 to September 2014. SD1 denotes the portfolio with the lowest standard deviation and SD25 denotes the portfolio with the highest standard deviation.

Panel A: Equally-weighted

	SD1	*SD2*	*SD3*	*SD4*	*SD5*	*SD6*	*SD7*	*SD8*	*SD9*	*SD10*	*SD11*	*SD12*	
mean	1.28	1.28	1.26	0.90	0.81	0.86	0.97	0.81	0.89	1.05	1.12	0.85	
sd	4.09	3.97	4.61	4.55	4.82	4.39	4.76	5.66	4.95	5.90	4.88	6.20	
median	1.39	1.54	1.51	1.24	1.27	1.42	1.65	1.14	1.43	1.29	1.32	1.42	
trimmed	1.35	1.52	1.33	1.19	1.00	1.07	1.27	0.96	1.21	1.06	1.33	1.05	
min	-16.91	-12.95	-20.60	-15.42	-17.02	-15.85	-22.18	-20.88	-20.32	-24.90	-18.57	-25.77	
max	16.75	12.93	24.44	22.23	19.07	17.07	22.17	32.78	17.39	40.40	19.72	35.17	
	SD13	*SD14*	*SD15*	*SD16*	*SD17*	*SD18*	*SD19*	*SD20*	*SD21*	*SD22*	*SD23*	*SD24*	*SD25*
mean	1.07	1.33	1.16	1.21	0.76	0.84	0.89	0.35	0.70	0.99	0.87	1.54	1.58
sd	5.81	6.59	6.01	5.93	6.12	6.32	6.86	7.20	7.23	6.74	9.24	10.73	9.50
median	1.59	1.53	1.12	1.58	1.13	1.08	0.69	-0.08	0.85	0.79	1.05	0.24	1.70
trimmed	1.16	1.34	1.26	1.33	0.89	0.91	0.95	0.26	0.84	0.94	0.57	0.41	1.25
min	-23.47	-22.31	-20.28	-18.82	-20.29	-28.83	-20.90	-26.71	-27.29	-18.92	-24.86	-19.41	-22.66
max	37.93	45.38	35.64	29.57	20.21	37.83	20.38	28.66	31.96	25.42	45.27	67.95	45.88

Panel B: Value-weighted

	SD1	*SD2*	*SD3*	*SD4*	*SD5*	*SD6*	*SD7*	*SD8*	*SD9*	*SD10*	*SD11*	*SD12*	
mean	0.83	1.14	0.74	0.65	0.67	0.33	0.61	-0.02	0.60	1.11	0.78	0.86	
sd	3.86	3.79	3.91	4.59	4.56	5.41	4.64	6.19	5.66	6.09	5.07	6.74	
median	1.28	1.29	1.04	0.97	0.82	1.15	0.58	0.32	0.89	1.00	1.07	1.60	
trimmed	1.03	1.35	0.91	0.82	0.83	0.73	0.69	0.35	0.79	1.33	0.92	1.05	
min	-16.32	-10.61	-13.87	-15.35	-15.57	-19.66	-18.16	-23.96	-28.29	-24.20	-15.63	-27.16	
max	8.79	10.57	14.65	15.56	11.55	16.83	16.39	16.86	20.49	26.44	15.98	25.74	
	SD13	*SD14*	*SD15*	*SD16*	*SD17*	*SD18*	*SD19*	*SD20*	*SD21*	*SD22*	*SD23*	*SD24*	*SD25*
mean	0.89	0.72	1.10	0.97	0.78	1.08	0.41	0.22	1.05	0.55	-0.25	0.29	-0.38
sd	5.96	7.00	6.53	7.04	7.15	7.02	8.99	8.63	8.05	8.89	9.91	9.43	12.44
median	1.18	1.37	1.47	1.39	1.23	2.06	1.29	0.29	0.98	0.56	0.71	0.48	0.94
trimmed	1.10	1.08	1.22	1.07	1.04	1.34	0.74	0.01	1.29	0.54	-0.07	0.32	0.06
min	-17.41	-37.40	-23.27	-21.82	-23.63	-24.32	-33.58	-22.06	-25.74	-25.76	-26.46	-26.61	-44.65
max	21.92	15.27	26.44	20.67	16.94	23.64	21.91	36.81	24.02	23.41	25.26	36.00	41.90

Table 4.7

Descriptive statistics for 25 size and momentum portfolios.

The table reports descriptive statistics for 25 intersecting size and momentum portfolios formed by using the whole sample of firms. Size portfolios are formed as follow: four from the largest 350 firms and one from the rest of the sample. Momentum portfolios are formed using the whole sample of firms. The first character of portfolio's name denotes size and the second denotes the momentum category. For example, SL denotes small size/low momentum, S2 denotes small size/second lowest momentum category. B, M and H denote big, middle and high, respectively.

Panel A: Equally-weighted

	SL	*S2*	*S3*	*S4*	*SH*	*S2L*	*S22*	*S23*	*S24*	*S2H*	*M3L*	*M32*	
mean	1.24	1.18	1.19	1.25	0.76	0.49	1.14	1.23	0.75	0.4	1.01	1.06	
sd	7.28	4.93	4.98	5.02	5.25	8.73	6.07	5.46	5.39	6.26	8.27	5.86	
median	1.1	1.39	1.62	1.34	1.54	0.59	1.56	1.72	1.36	1.18	0.88	1.42	
trimmed	1.01	1.23	1.32	1.3	0.96	0.19	1.35	1.35	1.05	1.17	0.96	1.21	
min	-24.79	-17.06	-18.17	-18.2	-18.2	-24.39	-15.39	-21.34	-20.09	-25.58	-25.62	-16.77	
max	44.94	25.15	29.15	24.82	19.12	54.69	28.59	29.14	17.14	14.23	55.09	22.17	
	M33	*M34*	*M3H*	*B4L*	*B42*	*B43*	*B44*	*B4H*	*BL*	*B2*	*B3*	*B4*	*BH*
mean	1.22	0.53	0.65	0.78	1	1.1	0.84	0.92	0.69	0.81	0.74	0.8	0.49
sd	5.48	6.54	7.24	7.62	6.03	5.85	5.1	7.18	6.86	4.94	4.14	4.33	6.71
median	1.42	0.76	2.16	1.13	1.32	1.26	1.56	1.37	1.05	1.39	1.08	1.34	1.19
trimmed	1.48	0.94	1.32	0.72	1.16	1.29	1.22	1.39	0.88	1.09	0.99	1.06	1.1
min	-21.46	-28.05	-34.77	-23.74	-23.5	-25.96	-17.97	-28.84	-19.19	-18.2	-13.78	-16.45	-25.51
max	16.12	34.18	28.38	29.11	32.21	22.52	12.69	23.83	25.39	16.19	10.61	11.07	19.92

Panel B: Value-weighted

	SL	*S2*	*S3*	*S4*	*SH*	*S2L*	*S22*	*S23*	*S24*	*S2H*	*M3L*	*M32*	
mean	1.08	1.23	1.19	1.29	0.82	0.51	1.1	1.29	0.78	0.39	0.99	1.05	
sd	7.26	5.25	5.66	5.22	5.71	8.81	5.94	5.49	5.33	6.26	8.35	5.88	
median	1.07	1.4	1.42	1.26	1.21	0.55	1.31	1.58	1.31	1.01	0.94	1.22	
trimmed	0.98	1.27	1.27	1.4	1	0.19	1.36	1.4	1.04	1.16	0.94	1.15	
min	-28.33	-18.08	-20.8	-19.09	-19.14	-25.08	-16.08	-20.38	-19.29	-25.57	-26.35	-15.88	
max	44.12	27.98	39.07	26.1	22.54	56.53	26.03	29.51	16.87	14.07	55.48	23.05	
	M33	*M34*	*M3H*	*B4L*	*B42*	*B43*	*B44*	*B4H*	*BL*	*B2*	*B3*	*B4*	*BH*
mean	1.2	0.51	0.66	0.85	1.02	1.12	0.82	1.07	0.73	0.69	0.53	0.56	0.4
sd	5.5	6.48	7.21	7.25	6.21	5.88	5.09	6.95	6.43	4.96	3.94	4.53	6.68
median	1.85	0.81	2.09	1.21	1.18	1.52	1.7	1.74	1.08	1.24	1.01	0.98	1.42
trimmed	1.44	0.89	1.38	0.83	1.23	1.32	1.19	1.45	0.82	0.9	0.74	0.82	1.00
min	-19.84	-26.09	-34.35	-22.49	-24.36	-26.43	-16.86	-26.42	-20.79	-18.29	-10.61	-22.31	-30.7
max	18.63	32.9	23.22	27.12	34.72	24.38	13.73	22.03	23.55	16.23	12.47	13.13	17.82

Table 4.8

Time-series regression with 10 value test portfolios.

The table reports results of time-series regression tests of 10 equally and value-weighted portfolios formed on book-to-market ratio. V1 denotes lowest value portfolio and V10 denotes the highest value portfolio. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*V1*	*V2*	*V3*	*V4*	*V5*	*V6*	*V7*	*V8*	*V9*	*V10*	*GRS*	*Mean R^2*
Panel A: Equally-weighted portfolios												
CAPM	-0.29%	0.07%	0.49%	0.34%	0.71%	0.61%	0.64%	0.65%	0.83%	1.23%	2.2792	0.6005
	(0.3112)	(0.7626)	(0.0135)	(0.122)	(0.0057)	(0.0088)	(0.0172)	(0.028)	(0.0085)	(0.0052)	(0.0158)	
FF	-0.20%	0.08%	0.38%	0.14%	0.44%	0.36%	0.29%	0.23%	0.42%	0.73%	2.4000	0.8599
	(0.2417)	(0.4942)	(0.0039)	(0.2457)	(0.0044)	(0.0091)	(0.0477)	(0.1584)	(0.0238)	(0.0204)	(0.011)	
4FF	-0.02%	0.17%	0.50%	0.20%	0.53%	0.44%	0.31%	0.27%	0.64%	0.93%	3.4525	0.8663
	(0.9101)	(0.1564)	(0.0002)	(0.1279)	(0.0009)	(0.0022)	(0.0400)	(0.1003)	(0.0005)	(0.004)	(0.0004)	
4FF_CMSI	1.52%	0.28%	1.36%	0.09%	1.47%	3.66%	1.93%	2.73%	3.38%	3.66%	1.9692	0.8680
	(0.2574)	(0.7624)	(0.1885)	(0.9299)	(0.2338)	(0.001)	(0.1002)	(0.0368)	(0.0178)	(0.1459)	(0.0399)	
4FF_ISENT	-0.04%	0.16%	0.49%	0.19%	0.51%	0.43%	0.29%	0.26%	0.62%	0.88%	3.4289	0.8694
	(0.8181)	(0.1836)	(0.0002)	(0.1391)	(0.0011)	(0.0028)	(0.048)	(0.1185)	(0.0007)	(0.0052)	(0.0004)	
4FF_ISENT_CMSI	-1.00%	-1.91%	-0.20%	-1.03%	-0.81%	3.63%	0.79%	1.88%	2.79%	-2.12%	1.3895	0.8702
	(0.5830)	(0.1327)	(0.8883)	(0.4582)	(0.6312)	(0.0166)	(0.6238)	(0.2924)	(0.1529)	(0.5313)	(0.1894)	
Panel B: Value-weighted portfolios												
CAPM	-0.14%	0.18%	0.19%	0.36%	0.32%	0.4%	0.39%	0.37%	0.37%	0.74%	1.8030	0.6264
	(0.4738)	(0.2581)	(0.3197)	(0.0734)	(0.1932)	(0.0781)	(0.1511)	(0.1706)	(0.2398)	(0.0904)	(0.0636)	
FF	0.13%	0.33%	0.2%	0.37%	0.32%	0.21%	0.24%	0.16%	0.02%	0.39%	1.6322	0.7004
	(0.337)	(0.0166)	(0.3013)	(0.0644)	(0.2016)	(0.3095)	(0.3565)	(0.5114)	(0.9477)	(0.3221)	(0.1016)	
4FF	0.24%	0.28%	0.11%	0.36%	0.08%	0.19%	0.42%	0.22%	0.11%	0.58%	1.7101	0.7073
	(0.0841)	(0.0454)	(0.5921)	(0.0838)	(0.745)	(0.3901)	(0.1221)	(0.3989)	(0.6841)	(0.1516)	(0.0824)	
4FF_CMSI	0.84%	1.10%	0.03%	-1.30%	-0.25%	2.27%	0.39%	0.31%	2.28%	2.30%	0.5801	0.7091
	(0.4442)	(0.3199)	(0.9838)	(0.4303)	(0.8977)	(0.1892)	(0.8536)	(0.8787)	(0.2912)	(0.4742)	(0.8286)	
4FF_ISENT	0.24%	0.27%	0.11%	0.36%	0.08%	0.17%	0.42%	0.22%	0.08%	0.57%	1.6553	0.7080
	(0.0861)	(0.0529)	(0.569)	(0.0881)	(0.739)	(0.4472)	(0.1193)	(0.3946)	(0.7600)	(0.1645)	(0.0956)	
4FF_ISENT_CMSI	1.26%	-0.1%	1.37%	-3.49%	-0.09%	-0.53%	1.34%	0.96%	-1.47%	0.49%	0.4590	0.7098
	(0.4031)	(0.9493)	(0.5256)	(0.1226)	(0.9748)	(0.8220)	(0.6456)	(0.7302)	(0.617)	(0.9124)	(0.9140)	

and only 20% significant intercepts for VW portfolios. However, the incremental adjusted R^2 is approximately 26% indicating the power of SMB and HML factors to explain stock returns. For Carhart (1997) model (4FF), results are similar to CAPM and reject the null hypothesis that all intercept terms are jointly equal zero.

The addition of the core managerial sentiment index (CMSI) to 4FF model improves results, with only 20% of EW and 0% of VW portfolios having significant intercepts. The significant intercepts are more concentrated in portfolios with high book-to-market ratios. 4FF_CMSI model fails the GRS for EW portfolios, however, the model provides highly insignificant intercepts for value-weighted portfolios. The addition of investor sentiment (ISENT) yields similar results to FF and 4FF models and fails GRS tests. However, utilising an asset pricing model that encompasses both investor and managerial sentiment strongly passes the GRS test. Incremental $adjusted - R^2$ is very small with increase of 0.08% in EW portfolios and 0.18% in VW portfolios.

Table 4.9 reports regression results for 10 EW and VW portfolios sorted on size. Simple CAPM yields significant alphas in 60% of equally-weighted and value-weighted test portfolios. We observe that CAPM fails to explain returns of small sized portfolios as indicated by the concentration of significant alphas in S1 to S6 portfolios. The GRS test statistics for CAPM indicates a rejection of the null hypothesis that alphas of EW portfolios jointly equal zero. For VW portfolios, CAPM passes the GRS test with p-value of 0.1987. Results for Fama & French (1993) three factor model and Carhart (1997) four factor model are different for size test portfolios. The two models fail to pass the GRS test for size portfolios with FF only passing the test for EW size portfolios. The distribution of insignificant intercept terms is comparable across all size portfolios for FF and 4FF models.

Similar to value portfolios, adding managerial sentiment index (CMSI) improve results for value-weighted size portfolios with GRS test statistic of 0.9 and p-value of 0.5339. The intercept terms for equally-weighted portfolios are significant in 50% of test portfolios and are concentrated in medium sized portfolios. The

Table 4.9
Time-series regression with 10 size test portfolios.

The table reports results of time-series regression tests of 10 equally and value-weighted portfolios formed on market capitalization. S1 denotes the smallest portfolio and S10 denotes the largest portfolio. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (*p*-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*GRS*	*Mean R^2*
Panel A: Equally-weighted portfolios												
CAPM	0.94%	0.74%	0.6%	0.73%	0.46%	0.59%	0.36%	0.29%	0.27%	0.24%	1.6989	0.5892
	(0.0112)	(0.0355)	(0.0672)	(0.0254)	(0.1174)	(0.037)	(0.1887)	(0.1992)	(0.1191)	(0.0234)	(0.0848)	
FF	0.70%	0.35%	0.28%	0.44%	0.15%	0.31%	0.11%	0.12%	0.17%	0.24%	1.6198	0.8262
	(0.0262)	(0.1076)	(0.1655)	(0.0228)	(0.327)	(0.0422)	(0.4085)	(0.4016)	(0.2134)	(0.0230)	(0.1050)	
4FF	0.72%	0.50%	0.35%	0.58%	0.25%	0.4%	0.25%	0.23%	0.32%	0.33%	2.7694	0.8318
	(0.0278)	(0.025)	(0.0969)	(0.003)	(0.1105)	(0.0114)	(0.0555)	(0.1106)	(0.016)	(0.0015)	(0.0035)	
4FF_CMSI	-0.05%	0.67%	2.33%	3.47%	3.54%	4.27%	0.98%	2.19%	1.73%	0.46%	2.5006	0.8336
	(0.9835)	(0.7055)	(0.1628)	(0.0228)	(0.0043)	(0.0000)	(0.3364)	(0.0561)	(0.0986)	(0.5742)	(0.0081)	
4FF_ISENT	0.7%	0.5%	0.34%	0.56%	0.24%	0.37%	0.24%	0.21%	0.31%	0.32%	2.7439	0.8349
	(0.0325)	(0.0267)	(0.1107)	(0.0039)	(0.1331)	(0.0149)	(0.0653)	(0.1368)	(0.0198)	(0.0019)	(0.0038)	
4FF_ISENT_CMSI	-4.94%	-0.01%	1.25%	1.5%	3%	1.88%	-0.36%	0.09%	0.42%	-0.84%	0.9449	0.8360
	(0.1604)	(0.9964)	(0.5851)	(0.4694)	(0.0756)	(0.2457)	(0.7963)	(0.9554)	(0.7708)	(0.4518)	(0.4940)	
Panel B: Value-weighted portfolios												
CAPM	0.18%	0.68%	0.62%	0.68%	0.5%	0.5%	0.4%	0.3%	0.33%	0.05%	1.369	0.5895
	(0.587)	(0.0384)	(0.0463)	(0.0401)	(0.0852)	(0.0551)	(0.1104)	(0.178)	(0.0387)	(0.5795)	(0.1987)	
FF	-0.08%	0.34%	0.36%	0.53%	0.23%	0.31%	0.2%	0.2%	0.25%	0.13%	1.9881	0.8457
	(0.7658)	(0.0996)	(0.0634)	(0.0057)	(0.1086)	(0.0212)	(0.0718)	(0.1182)	(0.0384)	(0.0342)	(0.0377)	
4FF	-0.08%	0.39%	0.33%	0.43%	0.19%	0.26%	0.19%	0.12%	0.26%	0.12%	1.6484	0.8468
	(0.7865)	(0.0642)	(0.0976)	(0.0263)	(0.2135)	(0.0619)	(0.0905)	(0.3481)	(0.04)	(0.0652)	(0.0974)	
4FF_CMSI	-0.61%	-0.13%	0.76%	-0.64%	1.8%	2.08%	0.06%	0.93%	1.48%	0.34%	0.9008	0.8480
	(0.7848)	(0.9363)	(0.6345)	(0.6776)	(0.1287)	(0.0542)	(0.9457)	(0.3648)	(0.134)	(0.5012)	(0.5339)	
4FF_ISENT	-0.09%	0.39%	0.33%	0.43%	0.18%	0.24%	0.19%	0.11%	0.25%	0.12%	1.6088	0.8473
	(0.7391)	(0.0633)	(0.1044)	(0.0284)	(0.2354)	(0.0761)	(0.0986)	(0.4016)	(0.0481)	(0.0729)	(0.1083)	
4FF_ISENT_CMSI	-4.55%	-0.02%	0.02%	-2.47%	1.52%	0.59%	-0.89%	-1.14%	0.37%	-0.07%	0.6655	0.8489
	(0.1333)	(0.9947)	(0.9943)	(0.2381)	(0.3508)	(0.6866)	(0.467)	(0.4146)	(0.7823)	(0.9172)	(0.7551)	

impact of adding ISENT is similar, but less powerful, to 4FF_CMSI for equally- and value-weighed size portfolios. The incremental increase in adjusted R^2 after adding CMSI (ISENT) is 0.18% (0.31%) for EW portfolios and 0.12% (0.05%) for VW portfolios. In both EW and VW, a model with ISENT and CMSI significantly passes the GRS test with incremental adjusted R^2 (compared to simple FF model) of 1.02% and 0.32% for EW and VW portfolios, respectively.[5]

Table 4.10 exhibits findings on the ability of asset pricing models to explain 25 portfolios returns sorted on the prior 12-month standard deviation of returns with SD1 denotes the least risky portfolio and SD25 is the riskiest portfolio. Panel A shows that all models fail the GRS test for equally-weighted volatility portfolios except of FF_ISNET_CMSI model which passes the test. It also shows that asset pricing models lack the ability to explain return portfolios with low risk characteristics as evidenced by the distribution of the insignificant alphas of each model. On the contrary, Carhart (1997) simple and sentiment-augmented models pass the GRS test for VW volatility portfolios with higher p-values are associated with managerial sentiment for the test and for all intercept terms.

Our final test portfolios are 25 (5 x 5) equally and value-weighted portfolios formed on book-to-market ratio and momentum. Table 4.11 shows the results for six asset pricing models that encompass both fundamental and behavioural factors. The first character of portfolio's name denotes size and the second denotes the momentum category. For example, SL denotes small size/low momentum, S2 denotes small size/second lowest momentum category and B, M and H denote big, middle and high, respectively. As reported in Table 4.11, our models mostly fail the GRS test for EW and VW size and momentum intersecting portfolios. The results are not very surprising since the poor performance of asset pricing models in explaining the returns of portfolios ranked based on momentum is already documented in previous research (Fletcher, 2010; Gregory et al., 2013). However, CMSI-augmented four factor models tested on equally-weighted portfolios pass the

[5] We also tested our models on 25 portfolios formed on the intersection between size and book-to-market value. The results do not change compared to size and value test portfolios, hence, not reported. However, we report their Hansen and Jagannathan results in Table 4.13. Results on models estimates and GRS test are available from authors upon request.

Table 4.10

Time-series regression with 25 standard deviation test portfolios.

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on volatility of prior 12 month returns. SD1(SD25) refers to portfolios with lowest (highest) prior 12-month standard deviation. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*SD1*	*SD2*	*SD3*	*SD4*	*SD5*	*SD6*	*SD7*	*SD8*	*SD9*	*SD10*
Panel A: Equally-weighted portfolios										
CAPM	0.89%	0.88%	0.83%	0.46%	0.37%	0.42%	0.54%	0.34%	0.44%	0.59%
	(0.0000)	(0.0000)	(3e-04)	(0.0253)	(0.1101)	(0.027)	(0.0265)	(0.225)	(0.0607)	(0.0663)
FF	0.79%	0.77%	0.59%	0.28%	0.15%	0.27%	0.31%	0.12%	0.23%	0.22%
	(0.0000)	(0.0000)	(0.0000)	(0.1091)	(0.3878)	(0.0564)	(0.0729)	(0.5944)	(0.1781)	(0.2907)
4FF	0.88%	0.82%	0.61%	0.28%	0.15%	0.29%	0.37%	0.2%	0.26%	0.35%
	(0.0000)	(0.0000)	(4e-04)	(0.1311)	(0.413)	(0.0459)	(0.038)	(0.3849)	(0.1435)	(0.1117)
4FF_CMSI	1.03%	0.41%	2.77%	-0.04%	2.34%	2.45%	1.13%	2.4%	3.03%	1%
	(0.5381)	(0.7902)	(0.0382)	(0.9758)	(0.1026)	(0.034)	(0.4169)	(0.1859)	(0.0277)	(0.5587)
4FF_ISENT	0.89%	0.83%	0.6%	0.27%	0.13%	0.29%	0.36%	0.19%	0.24%	0.34%
	(0.0000)	(0.0000)	(0.0000)	(0.1355)	(0.4673)	(0.0504)	(0.0398)	(0.3997)	(0.1647)	(0.122)
4FF_ISENT_CMSI	2.57%	2.06%	2.47%	-0.74%	0.77%	3.35%	1.41%	3.25%	2.77%	-0.19%
	(0.2637)	(0.3247)	(0.1773)	(0.7105)	(0.6913)	(0.0349)	(0.4589)	(0.1915)	(0.141)	(0.9364)
Panel B: Value-weighted portfolios										
CAPM	0.46%	0.77%	0.36%	0.23%	0.24%	-0.11%	0.19%	-0.51%	0.14%	0.64%
	(0.0473)	(0.0000)	(0.1076)	(0.3248)	(0.2857)	(0.7099)	(0.4338)	(0.0956)	(0.6378)	(0.0561)
FF	0.52%	0.89%	0.37%	0.29%	0.22%	-0.22%	0.12%	-0.42%	0.09%	0.55%
	(0.0248)	(0.0000)	(0.0911)	(0.2275)	(0.3442)	(0.4446)	(0.6116)	(0.1579)	(0.7681)	(0.0976)
4FF	0.55%	0.88%	0.33%	0.29%	0.15%	-0.04%	0.1%	-0.15%	0.08%	0.3%
	(0.023)	(0.0000)	(0.1411)	(0.2331)	(0.5395)	(0.9036)	(0.7031)	(0.6136)	(0.7871)	(0.38)
4FF_CMSI	0.53%	-1.02%	1.35%	-0.3%	-0.16%	1.88%	3.59%	3.43%	1.58%	-3.66%
	(0.7796)	(0.5515)	(0.4509)	(0.8772)	(0.9304)	(0.4203)	(0.0728)	(0.1428)	(0.527)	(0.1677)
4FF_ISENT	0.55%	0.89%	0.33%	0.29%	0.13%	-0.03%	0.09%	-0.16%	0.08%	0.31%
	(0.0222)	(0.0000)	(0.15)	(0.2374)	(0.5888)	(0.9104)	(0.7300)	(0.5999)	(0.8105)	(0.3606)
4FF_ISENT_CMSI	1.63%	-0.82%	1%	-1.12%	-3.96%	4.06%	4.91%	5.33%	1.04%	-4.57%
	(0.5295)	(0.7282)	(0.684)	(0.6751)	(0.122)	(0.2053)	(0.0738)	(0.0978)	(0.7611)	(0.2106)

Table 4.10

Time-series regression with 25 standard deviation test portfolios **(Continued).**

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on volatility of prior 12 month returns. SD1(SD25) refers to portfolios with lowest (highest) prior 12-month standard deviation. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*SD11*	*SD12*	*SD13*	*SD14*	*SD15*	*SD16*	*SD17*	*SD18*	*SD19*	*SD20*
Panel A: Equally-weighted portfolios										
CAPM	0.66%	0.35%	0.58%	0.82%	0.68%	0.74%	0.27%	0.35%	0.39%	-0.18%
	(0.0020)	(0.2255)	(0.0348)	(0.0124)	(0.0277)	(0.0154)	(0.3851)	(0.289)	(0.2806)	(0.6055)
FF	0.48%	0.08%	0.32%	0.49%	0.39%	0.4%	-0.03%	0.08%	0.13%	-0.47%
	(0.0017)	(0.692)	(0.082)	(0.0232)	(0.0529)	(0.0632)	(0.9112)	(0.7239)	(0.6235)	(0.0765)
4FF	0.52%	0.25%	0.43%	0.66%	0.55%	0.51%	0.07%	0.18%	0.32%	-0.36%
	(0.001)	(0.2157)	(0.0229)	(0.0029)	(0.0066)	(0.0216)	(0.7633)	(0.4281)	(0.2429)	(0.182)
4FF_CMSI	2.71%	0.61%	4.36%	5.24%	3.31%	3.85%	1.44%	2.37%	0.74%	0.56%
	(0.0267)	(0.6965)	(0.003)	(0.0022)	(0.037)	(0.0258)	(0.4458)	(0.1802)	(0.7366)	(0.7935)
4FF_ISENT	0.5%	0.23%	0.41%	0.62%	0.53%	0.49%	0.08%	0.15%	0.32%	-0.39%
	(0.0013)	(0.2385)	(0.0285)	(0.0038)	(0.0083)	(0.0261)	(0.7521)	(0.4951)	(0.2555)	(0.1511)
4FF_ISENT_CMSI	2.05%	-1.41%	3.87%	2.52%	1.8%	3.2%	3.42%	-0.98%	-0.39%	-3.69%
	(0.2197)	(0.5120)	(0.0534)	(0.2748)	(0.4052)	(0.1761)	(0.1880)	(0.6821)	(0.8979)	(0.2069)
Panel B: Value-weighted portfolios										
CAPM	0.33%	0.34%	0.41%	0.2%	0.6%	0.45%	0.24%	0.57%	-0.18%	-0.36%
	(0.1719)	(0.3026)	(0.1563)	(0.5792)	(0.0663)	(0.2089)	(0.467)	(0.1257)	(0.6924)	(0.4195)
FF	0.27%	0.22%	0.41%	0.28%	0.28%	0.16%	0.22%	0.53%	-0.25%	-0.44%
	(0.2629)	(0.4949)	(0.1424)	(0.4325)	(0.3121)	(0.6242)	(0.5056)	(0.1404)	(0.5563)	(0.2793)
4FF	0.09%	0.21%	0.34%	0.1%	0.37%	0.2%	0.23%	0.44%	0.14%	-0.3%
	(0.6996)	(0.5281)	(0.2358)	(0.7911)	(0.2097)	(0.5506)	(0.4985)	(0.2311)	(0.7455)	(0.4631)
4FF_CMSI	1.12%	-0.44%	3.28%	-0.49%	0.84%	0.47%	-2.92%	2.41%	-0.76%	1.19%
	(0.5669)	(0.8687)	(0.148)	(0.8645)	(0.7163)	(0.8599)	(0.2799)	(0.4116)	(0.8237)	(0.7169)
4FF_ISENT	0.08%	0.21%	0.33%	0.08%	0.35%	0.21%	0.23%	0.41%	0.15%	-0.33%
	(0.747)	(0.5323)	(0.2566)	(0.8199)	(0.2274)	(0.5318)	(0.5063)	(0.2648)	(0.7277)	(0.4219)
4FF_ISENT_CMSI	-1.09%	-1.27%	3.04%	-3.69%	-1.38%	2.75%	-6.36%	-2.36%	0.58%	-3.17%
	(0.6821)	(0.727)	(0.3286)	(0.3526)	(0.6626)	(0.4516)	(0.0857)	(0.5554)	(0.9011)	(0.4809)

Table 4.10

Time-series regression with 25 standard deviation test portfolios **(Continued).**

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on volatility of prior 12 month returns. SD1(SD25) refers to portfolios with lowest (highest) prior 12-month standard deviation. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*SD21*	*SD22*	*SD23*	*SD24*	*SD25*	*GRS*	*Mean R^2*
Panel A: Equally-weighted portfolios							
CAPM	0.18%	0.51%	0.31%	1.04%	1.07%	2.4145	0.5373
	(0.6401)	(0.1786)	(0.5662)	(0.1518)	(0.0831)	(0.0000)	
FF	-0.12%	0.28%	0.01%	0.78%	0.91%	2.5127	0.7395
	(0.6397)	(0.3605)	(0.9781)	(0.2274)	(0.0839)	(0.0000)	
4FF	0.04%	0.54%	0.31%	0.76%	1.27%	3.0118	0.7452
	(0.8873)	(0.0874)	(0.4554)	(0.2611)	(0.0191)	(0.0000)	
4FF_CMSI	0.02%	6.69%	6.55%	-11.83%	-0.97%	1.8889	0.7485
	(0.9925)	(0.0067)	(0.046)	(0.0247)	(0.8188)	(0.0108)	
4FF_ISENT	0.02%	0.5%	0.26%	0.78%	1.24%	2.9706	0.7486
	(0.9403)	(0.1088)	(0.53)	(0.249)	(0.0219)	(0.0000)	
4FF_ISENT_CMSI	-3.49%	3.81%	1.45%	-18.62%	-8.13%	1.2786	0.7500
	(0.2171)	(0.2549)	(0.7453)	(0.0099)	(0.1605)	(0.1855)	
Panel B: Value-weighted portfolios							
CAPM	0.48%	-0.02%	-0.83%	-0.28%	-1.03%	1.7496	0.5190
	(0.2234)	(0.9707)	(0.1515)	(0.6047)	(0.1653)	(0.0218)	
FF	0.51%	0.05%	-0.91%	-0.26%	-0.91%	1.6276	0.5746
	(0.176)	(0.9119)	(0.073)	(0.5715)	(0.1366)	(0.0400)	
4FF	0.51%	0.33%	-0.66%	-0.35%	-0.72%	1.4011	0.5811
	(0.1985)	(0.5022)	(0.2014)	(0.4645)	(0.2509)	(0.1123)	
4FF_CMSI	-1.87%	3.26%	-2.79%	0.87%	-3.56%	0.7567	0.5828
	(0.5475)	(0.4005)	(0.4949)	(0.819)	(0.4755)	(0.7896)	
4FF_ISENT	0.48%	0.29%	-0.66%	-0.37%	-0.76%	1.3935	0.5830
	(0.2209)	(0.5498)	(0.2046)	(0.4486)	(0.2255)	(0.1162)	
4FF_ISENT_CMSI	-8.88%	-1.41%	-4.29%	-0.8%	-14.1%	1.1226	0.5858
	(0.0357)	(0.7902)	(0.4457)	(0.8778)	(0.0379)	(0.3251)	

GRS test with significant intercept terms which are more concentrated in small portfolios with low momentum characteristics. This indicates that models are more able to explain returns of big companies whose stock returns exhibit high momentum. In sum, all our tests show the powerful impact of adding managerial sentiment to asset pricing models, specifically when testing value-weighted portfolios. A summary of alphas and GRS results for test portfolios is reported in Table 4.12.

The results of Hansen and Jagannathan (HJ) test confirms previous results as shown by Table 4.13. The table reports the HJ distance (δ) with the associated standard errors for the six asset pricing models. The reported results show a significant improve in ability of asset pricing models in explaining the cross-sectional variation of stock returns after incorporating our managerial sentiment proxy. For equally (value) weighted portfolios, models contain the CMSI yields a reduction of 0.5991 (0.7255) in the pricing error distance relative to the capital asset pricing model (CAPM). These findings suggest a significant improvement for managerial sentiment-augmented asset pricing model. We report the mean and standard deviation of the stochastic discount factor of each model against the Hansen and Jagannathan bound in Figure 4.1.[6]

4.5. Sentiment and size, value and momentum premiums

Firm characteristics represent important factors in determining the relationship between investor sentiment and stock returns. Lee et al. (1991) provide evidence that stocks of small sized firms are more prone to sentiment relative to big firms. Further, Baker & Wurgler (2006) show that investor sentiment is more strongly associated with small firms, extreme growth stocks and unprofitable stocks. Our aim in this section is to test whether proxies for investor as

[6] In Figure 4.1, we use 10 value-weighted book-to-market portfolios to construct the HJ bound and the stochastic discount factor of each model. Similar figures for other equally and value-weighted portfolios are available from the author upon request.

Table 4.11

Time-series regression with 25 size and momentum test portfolios.

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on size and momentum. The first character of portfolio's name denotes size and the second denotes the momentum category. For example, SL denotes small size/low momentum, S2 denotes small size/second lowest momentum category. B, M and H denote big, middle and high, respectively. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*SL*	*S2*	*S3*	*S4*	*SH*	*S2L*	*S22*	*S23*	*S24*	*S2H*
Panel A: Equally-weighted portfolios										
CAPM	0.76%	0.76%	0.79%	0.84%	0.33%	-0.04%	0.67%	0.79%	0.3%	-0.09%
	(0.0817)	0.006	(0.0102)	(0.0052)	(0.2721)	(0.9372)	(0.0411)	0.01	(0.2888)	(0.7698)
FF	0.31%	0.51%	0.48%	0.65%	0.2%	-0.63%	0.42%	0.52%	0.07%	-0.14%
	(0.3022)	(0.0077)	(0.0299)	(0.0039)	(0.3523)	0.072	(0.0859)	(0.0124)	0.77	(0.6139)
4FF	0.61%	0.55%	0.55%	0.66%	0.17%	-0.21%	0.4%	0.47%	0.16%	0.09%
	(0.0417)	(0.0055)	(0.0149)	(0.0046)	0.447	0.543	(0.1141)	(0.0312)	(0.5218)	(0.7583)
4FF_CMSI	2.21%	1.42%	0.53%	1.57%	0.75%	1.35%	4.34%	4.91%	0.9%	1.34%
	(0.3461)	(0.3632)	(0.7668)	(0.3877)	(0.6763)	(0.6122)	(0.0296)	(0.0036)	(0.6401)	0.543
4FF_ISENT	0.59%	0.54%	0.55%	0.65%	0.17%	-0.23%	0.4%	0.45%	0.15%	0.09%
	(0.0476)	(0.0067)	(0.0155)	(0.0053)	(0.4638)	(0.5044)	(0.1169)	(0.0359)	(0.5273)	0.759
4FF_ISENT_CMSI	0.38%	-0.63%	0.3%	0.26%	0.11%	-1.27%	7.55%	6.46%	1.28%	2.48%
	(0.9072)	(0.7698)	0.902	(0.9172)	(0.9639)	(0.7282)	(0.0057)	(0.0051)	(0.6284)	(0.4136)
Panel B: Value-weighted portfolios										
CAPM	0.58%	0.79%	0.77%	0.88%	0.39%	-0.02%	0.63%	0.85%	0.34%	-0.1%
	(0.1582)	(0.0059)	0.027	(0.0054)	(0.2521)	(0.9632)	(0.0471)	(0.0062)	(0.2313)	0.751
FF	0.11%	0.51%	0.42%	0.67%	0.26%	-0.63%	0.4%	0.58%	0.1%	-0.15%
	(0.6791)	(0.0107)	(0.0864)	(0.0046)	(0.2748)	(0.0714)	0.096	(0.0063)	(0.6605)	(0.5837)
4FF	0.39%	0.54%	0.5%	0.72%	0.28%	-0.23%	0.39%	0.53%	0.18%	0.09%
	0.122	(0.0081)	(0.0475)	(0.0033)	(0.2637)	(0.5058)	(0.1146)	(0.0151)	(0.4454)	(0.7528)
4FF_CMSI	5.73%	2.29%	0.49%	2.47%	2.03%	1.6%	4.17%	5.38%	0.84%	1.36%
	0.004	(0.1555)	(0.8041)	(0.1977)	(0.3027)	(0.5527)	(0.0325)	(0.0016)	(0.6575)	(0.5367)
4FF_ISENT	0.36%	0.53%	0.5%	0.71%	0.27%	-0.25%	0.39%	0.52%	0.18%	0.09%
	(0.1499)	(0.0097)	(0.0506)	(0.0038)	(0.2806)	(0.4685)	0.115	0.018	(0.4505)	(0.7543)
4FF_ISENT_CMSI	3.93%	1.43%	-0.52%	1.96%	1.8%	-0.85%	7.75%	6.72%	1.17%	2.45%
	(0.1458)	(0.5163)	(0.8504)	(0.4561)	(0.5063)	(0.8173)	(0.0036)	(0.0039)	(0.6539)	(0.4169)

Table 4.11

Time-series regression with 25 size and momentum test portfolios **(Continued).**

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on size and momentum. The first character of portfolio's name denotes size and the second denotes the momentum category. For example, SL denotes small size/low momentum, S2 denotes small size/second lowest momentum category. B, M and H denote big, middle and high, respectively. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*M3L*	*M32*	*M33*	*M34*	*M3H*	*B4L*	*B42*	*B43*	*B44*	*B4H*
Panel A: Equally-weighted portfolios										
CAPM	0.46%	0.59%	0.75%	0.01%	0.15%	0.23%	0.51%	0.59%	0.38%	0.38%
	(0.3106)	(0.0509)	(0.0037)	(0.9695)	(0.7079)	(0.5405)	(0.0777)	0.012	(0.0806)	(0.2655)
FF	-0.02%	0.26%	0.53%	-0.23%	0.3%	-0.14%	0.21%	0.38%	0.32%	0.45%
	(0.9441)	(0.2329)	(0.0107)	(0.3187)	(0.3424)	(0.6607)	(0.3666)	(0.0486)	(0.0788)	(0.1025)
4FF	0.28%	0.41%	0.53%	-0.03%	0.27%	0.17%	0.46%	0.47%	0.36%	0.45%
	(0.3796)	(0.0673)	(0.0151)	(0.8914)	(0.4033)	(0.5898)	(0.0398)	(0.0171)	(0.0581)	(0.1109)
4FF_CMSI	3.12%	1.56%	2.08%	-0.24%	2.64%	2.39%	5.22%	1.54%	1.77%	0.41%
	(0.2086)	(0.3724)	(0.2202)	(0.8972)	(0.3077)	(0.3415)	0.003	(0.3218)	(0.2387)	(0.8544)
4FF_ISENT	0.25%	0.4%	0.52%	-0.02%	0.25%	0.15%	0.44%	0.46%	0.35%	0.42%
	(0.4323)	(0.0705)	(0.0159)	(0.9153)	(0.4452)	(0.6442)	(0.0497)	(0.0197)	(0.0655)	(0.1351)
4FF_ISENT_CMSI	-0.57%	1.97%	3.11%	0.96%	-0.09%	-0.63%	4.15%	0.46%	1.06%	-6.34%
	(0.8672)	(0.4113)	(0.1822)	(0.7033)	(0.9789)	(0.8536)	(0.0822)	(0.8307)	(0.6069)	(0.0353)
Panel B: Value-weighted portfolios										
CAPM	0.44%	0.58%	0.72%	-0.01%	0.16%	0.31%	0.53%	0.61%	0.36%	0.53%
	(0.3398)	(0.0524)	(0.0055)	(0.9841)	(0.6966)	(0.3687)	(0.0832)	(0.0094)	(0.1005)	(0.1028)
FF	-0.05%	0.25%	0.52%	-0.24%	0.31%	-0.04%	0.22%	0.39%	0.29%	0.59%
	(0.8734)	(0.2451)	(0.0148)	(0.3078)	(0.3097)	(0.8944)	(0.3651)	(0.0442)	(0.1286)	(0.0286)
4FF	0.27%	0.4%	0.56%	-0.02%	0.29%	0.24%	0.49%	0.48%	0.34%	0.54%
	(0.4037)	(0.0701)	(0.0112)	(0.9169)	(0.3638)	(0.3995)	(0.0426)	0.016	(0.0833)	(0.0507)
4FF_CMSI	3.06%	0.87%	2.12%	-0.24%	1.88%	3.05%	5.62%	1.36%	1.93%	1.06%
	(0.2378)	0.617	(0.2236)	(0.8938)	(0.4555)	(0.1819)	0.003	(0.3829)	(0.2162)	(0.6287)
4FF_ISENT	0.24%	0.4%	0.56%	-0.02%	0.27%	0.21%	0.46%	0.47%	0.33%	0.51%
	(0.4553)	(0.0721)	(0.0119)	(0.9343)	(0.3985)	(0.4569)	(0.0531)	(0.0184)	(0.0933)	(0.0632)
4FF_ISENT_CMSI	-0.55%	1.04%	3.01%	0.55%	-0.81%	-0.53%	4.5%	0.2%	1.26%	-5.22%
	(0.8765)	0.664	(0.2072)	(0.8262)	(0.8139)	(0.8646)	(0.0812)	(0.9264)	(0.5548)	(0.0761)

Table 4.11

Time-series regression with 25 size and momentum test portfolios **(Continued).**

The table reports results of time-series regression tests of 25 equally and value-weighted portfolios formed on size and momentum. The first character of portfolio's name denotes size and the second denotes the momentum category. For example, SL denotes small size/low momentum, S2 denotes small size/second lowest momentum category. B, M and H denote big, middle and high, respectively. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models intercept terms (α) are reported in percentages (%) and their significance statistics (p-values) are reported in parenthesis. We use GRS test statistics to test the null hypothesis that all intercept terms are jointly zero with p-value reported in parenthesis. Mean R^2 denotes the mean adjusted R-squared of each regression.

Portfolio	*BL*	*B2*	*B3*	*B4*	*BH*	*GRS*	*Mean* R^2
Panel A: Equally-weighted portfolios							
CAPM	0.16%	0.34%	0.3%	0.36%	-0.02%	2.2626	0.5566
	(0.6097)	(0.0706)	(0.0354)	(0.0404)	(0.9494)	(0.0014)	
FF	-0.11%	0.22%	0.24%	0.4%	0.19%	2.1796	0.7372
	(0.7032)	(0.2182)	(0.0912)	(0.0248)	(0.5397)	(0.0022)	
4FF	0.17%	0.28%	0.26%	0.29%	0.45%	1.9229	0.7464
	(0.5488)	(0.1294)	(0.0757)	(0.1012)	(0.1363)	(0.0090)	
4FF_CMSI	1.77%	1.81%	-0.24%	0.01%	-0.16%	1.1149	0.7481
	(0.4249)	(0.2106)	(0.8344)	(0.9933)	(0.9484)	(0.3333)	
4FF_ISENT	0.15%	0.27%	0.27%	0.29%	0.45%	1.9059	0.7480
	(0.5837)	(0.1372)	0.075	(0.1091)	(0.1397)	(0.0099)	
4FF_ISENT_CMSI	0.33%	2.26%	-0.36%	-1.4%	-1.09%	1.1118	0.7497
	(0.9131)	(0.2549)	(0.8239)	(0.4717)	(0.7411)	(0.3368)	
Panel B: Value-weighted portfolios							
CAPM	0.22%	0.24%	0.13%	0.13%	-0.09%	2.2143	0.5364
	(0.4604)	(0.2761)	(0.5209)	(0.5614)	(0.7904)	(0.0018)	
FF	0.1%	0.17%	0.22%	0.22%	0.15%	2.0229	0.7167
	(0.7331)	(0.4321)	(0.2568)	(0.3339)	(0.6614)	(0.0052)	
4FF	0.41%	0.17%	0.29%	0.08%	0.4%	1.8111	0.7267
	(0.1476)	(0.4565)	(0.1347)	(0.7167)	(0.2364)	(0.0161)	
4FF_CMSI	3.03%	0.96%	0.75%	0.27%	-0.82%	1.5197	0.7288
	(0.1785)	(0.5847)	(0.6317)	(0.8836)	(0.7595)	(0.0666)	
4FF_ISENT	0.39%	0.15%	0.3%	0.08%	0.41%	1.7934	0.7288
	(0.1676)	0.491	0.134	(0.7196)	(0.2346)	(0.0177)	
4FF_ISENT_CMSI	1.33%	-0.8%	1.5%	0.33%	-1.26%	1.1809	0.7304
	(0.6666)	(0.7418)	(0.4814)	(0.8975)	(0.7325)	(0.2665)	

Table 4.12

Summary of GRS results for asset pricing models tested on equally and value-weighted portfolios

The table summarize the comparative performance of alternative specifications of asset pricing models. Models are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Models are tested against equally and value-weighted portfolios formed on value, size, standard deviation and intersecting portfolios of book-to-market ratio and momentum factors. EW and VW denote equally and value-weighted test portfolios. Fail (Pass) refers to whether the GRS test reject (fail to reject) the null hypothesis that all portfolios alphas are jointly equal zero. Figures in parentheses refers to the percentage of insignificant alphas of each test portfolio. $\%\alpha^{INS}$ refers to the percentage of insignificant intercepts of all equally and value-weighted test portfolios. % GRS^{pass} reports the percentage of test portfolios formed on value, size, standard deviation and intersecting portfolios of book-to-market ratio and momentum factors that passed the GRS test. For example, 25% indicates that the model passes the GRS test for only one of four sets of test portfolios (i.e. value, size, sd and size/momentum test portfolios).

Model/Portfolios	10 value		10 size		25 SD		25 size/ momentum		$\%\alpha^{INS}$		% GRS^{pass}	
	EW	*VW*	*EW*	*VW*	*EW*	*VW*	*EW*	*VW*	*EW*	*VW*	*EW*	*VW*
CAPM	Fail	Fail	Fail	Pass	Fail	Fail	Fail	Fail	39%	62%	0%	25%
	(30%)	(70%)	(40%)	(40%)	(44%)	(76%)	(40%)	(60%)				
FF	Fail	Pass	Pass	Fail	Fail	Fail	Fail	Fail	51%	62%	25%	25%
	(40%)	(80%)	(60%)	(30%)	(52%)	(76%)	(52%)	(60%)				
4FF	Fail	Fail	Fail	Fail	Fail	Pass	Fail	Fail	41%	62%	0%	25%
	(40%)	(70%)	(20%)	(30%)	(52%)	(92%)	(52%)	(56%)				
4FF_CMSI	Fail	Pass	Fail	Pass	Fail	Pass	Pass	Fail	66%	91%	25%	75%
	(70%)	(100%)	(50%)	(90%)	(56%)	(92%)	(88%)	(80%)				
4FF_ISENT	Fail	Fail	Fail	Pass	Fail	Pass	Fail	Fail	45%	66%	0%	50%
	(40%)	(70%)	(30%)	(40%)	(56%)	(96%)	(52%)	(56%)				
4FF_ISENT_-CMSI	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	88%	91%	100%	100%
	(90%)	(100%)	(90%)	(100%)	(88%)	(80%)	(84%)	(84%)				

Table 4.13

Hansen and Jagannathan model specification tests

The table reports results of Hansen and Jagannathan distance (δ) for six asset pricing models. Models tested are the traditional capital asset pricing model (CAPM), Fama & French (1993) three factor model (FF), Carhart (1997) four factor model (4FF), 4FF model plus managerial sentiment (4FF_CMSI), 4FF plus investor sentiment (4FF_ISENT) and 4FF plus investor sentiment and managerial sentiment (4FF_ISENT_CMSI). Figures in parentheses are standard errors of δ. δ^{INC} denotes the incremental average reduction in HJ distance due to adding more factors to the base model (CAPM). For example, δ^{INC} for FF3 model tested on equally-weighted portfolios, is the average of HJ distances of all portfolios used in FF3 minus the average of HJ distances of all portfolios used in CAPM.

Model	*CAPM*	*FF*	*FF4*	*FF4_CMSI*	*FF4_ISENT*	*FF4 _ISENT_CMSI*
Panel A: Equally-weighted portfolios						
10 book-to-market portfolios	0.3649	0.2604	0.2554	0.1917	0.2445	0.0329
	(0.1003)	(0.1702)	(0.1328)	(0.5358)	0.202	(0.9985)
10 size portfolios	0.2033	0.2030	0.1800	0.1377	0.1389	0.0804
	(0.6165)	(0.3387)	(0.5332)	(0.4438)	(0.8126)	(0.8516)
25 standard deviation portfolios	0.4685	0.4674	0.4245	0.3490	0.4243	0.3473
	(0.1026)	(0.0737)	0.342	(0.5511)	0.301	(0.4841)
25 size/momentum portfolios	0.5232	0.5027	0.4800	0.4195	0.4280	0.3859
	0.077	(0.0739)	(0.1039)	(0.0714)	0.509	0.285
25 size/book-to-market portfolios	0.5704	0.5067	0.4737	0.4333	0.4649	0.4097
	(0.0306)	(0.0928)	(0.2097)	(0.0583)	(0.1879)	0.065
δ^{INC}	———	-0.1901	-0.3167	-0.5991	-0.4297	-0.8741
Panel B: Value-weighted portfolios						
10 book-to-market portfolios	0.2082	0.1657	0.1540	0.1030	0.1411	0.0927
	(0.8233)	(0.8156)	(0.7563)	(0.7119)	(0.7787)	(0.7584)
10 size portfolios	0.2493	0.2364	0.1563	0.1446	0.1550	0.1325
	(0.4616)	(0.3153)	(0.8595)	(0.5851)	0.733	(0.5431)
25 standard deviation portfolios	0.5781	0.5658	0.5369	0.3459	0.4861	0.3282
	(0.0233)	(0.0215)	(0.0785)	(0.3563)	(0.4844)	(0.6262)
25 size/momentum portfolios	0.5547	0.5312	0.4828	0.4084	0.4619	0.3965
	(0.0539)	(0.0483)	(0.1608)	(0.1547)	(0.2866)	(0.1682)
25 size/book-to-market portfolios	0.5704	0.5067	0.4737	0.4333	0.4649	0.4097
	(0.0306)	(0.0928)	(0.2097)	(0.0583)	(0.1879)	0.065
δ^{INC}	———	-0.1549	-0.3570	-0.7255	-0.4517	-0.8011

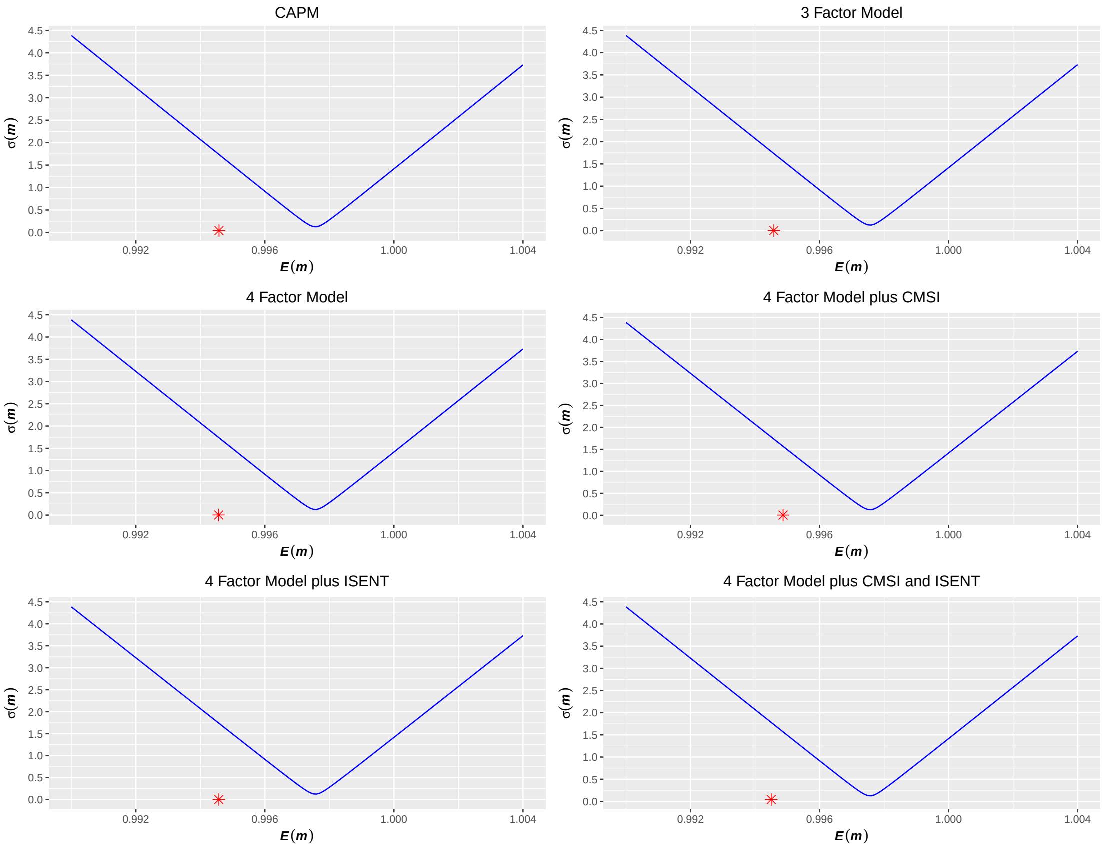

Figure 4.1: Hansen-Jagannathan Bounds

well as managerial sentiment forecast time-series variation in the size, value and momentum premiums. Following Lemmon & Portniaguina (2006), we estimate models in equations 10 and 11 over one, three, six and twelve months forecasting horizons using OLS and we assess the statistical significance of our estimates using Newey-West standard errors. As reported by Table 4.14, one and three month lagged measures of managerial sentiment index can forecast the size premium. The negative relationship between lagged values of CMSI and SMB is consistent with De Long et al. (1990) and Lemmon & Portniaguina (2006) results, which indicate that small stocks earn low returns following periods with higher sentiment. However, the ability of our measure of investor sentiment (ISENT) to forecast the size premium is only restricted to three-month forecasting horizon.

As shown by Table 4.15, forecasting models for value premium present interesting results for investor as well as managerial sentiment. Lagged measures of CMSI and ISENT exhibit forecasting power of value premium but only over

Table 4.14

Predictive regressions for size premium

The table reports the results of fitting models in equations 4.10 and 4.11 with "Factor" terms set to SMB premium. We tested the models over one, three, six and twelve months forecasting horizons. The first-row reports lagged explanatory variables of the model, with SENT is either ISENT when testing model 4.10 or CMSI when testing model 4.11. ISENT is a proxy for investor sentiment and calculated using principal component analysis (PCA) of three measures of investor sentiment; the number of initial public offerings, closed-end fund discounts and FTSE100 volatility index. CMSI is a proxy for managerial sentiment. RMRF is the market risk premium, SMB is the size risk premium, HML is the value risk premium and MOM reflects the momentum effect. T-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT and GDP are percentage change in industrial production level and the GDP growth rate, respectively. Data covers the period from January 2000 to September 2014 for the UK market. The table reports coefficients' estimates and [p-values] for each model. Incremental $R^2(Inc-R^2)$ is the difference between the adjusted R^2 $(Adj-R^2)$ of the model and a basic model that does not include sentiment indices.

	(Intercept)	SMB_{t-i}	$SENT_{t-i}$	$T-bill_{t-i}$	$T-spread_{t-i}$	$UNEMP_{t-i}$	IPT_{t-i}	GDP_{t-i}	$Adj-R^2$	$Inc-R^2$
Panel A: one-month										
$CMSI_{t-1}$	0.1622	0.0260	-0.0010	-0.0075	-0.0069	-0.0119	-0.0005	0.0134	0.0494	0.0347
	[0.0097**]	[0.7073]	[0.0166*]	[0.0107*]	[0.0298*]	[0.0713.]	[0.8605]	[0.0147*]		
$ISENT_{t-1}$	0.0424	0.0473	-0.0027	-0.0070	-0.0052	-0.0051	-0.0004	0.0080	0.0159	0.0012
	[0.1769]	[0.4689]	[0.3445]	[0.0368*]	[0.1482]	[0.3914]	[0.8826]	[0.2043]		
Panel B: three-month										
$CMSI_{t-3}$	0.1502	-0.1114	-0.0010	-0.0062	-0.0075	-0.0082	-0.0017	0.0104	0.0355	0.0385
	[0.0052**]	[0.1660]	[0.0087**]	[0.0163*]	[0.0177*]	[0.1688]	[0.5266]	[0.202]		
$ISENT_{t-3}$	0.0444	-0.0988	-0.0060	-0.0076	-0.0088	-0.0037	-0.0014	0.0075	0.0271	0.0301
	[0.1335]	[0.235]	[0.0182*]	[0.0101*]	[0.0165*]	[0.513]	[0.5865]	[0.3229]		
Panel C: six-month										
$CMSI_{t-6}$	0.0684	0.0099	-0.0005	-0.0025	-0.0052	-0.0005	-0.0012	-0.0007	-0.0071	0.0063
	[0.2471]	[0.9198]	[0.1877]	[0.3399]	[0.1592]	[0.9352]	[0.6157]	[0.9038]		
$ISENT_{t-6}$	0.0009	0.0236	0.0001	-0.0017	-0.0030	0.0034	-0.0012	-0.0047	-0.0196	-0.0062
	[0.9793]	[0.8053]	[0.971]	[0.6129]	[0.5276]	[0.5725]	[0.6274]	[0.4801]		
Panel D: twelve-month										
$CMSI_{t-12}$	0.0352	0.0410	-0.0002	-0.0014	-0.0016	-0.0013	0.0029	0.0017	-0.0263	-0.0044
	[0.4426]	[0.5844]	[0.4703]	[0.6911]	[0.7742]	[0.8187]	[0.3777]	[0.7138]		
$ISENT_{t-12}$	0.0117	0.0442	-0.0011	-0.0018	-0.0016	-0.0006	0.0029	0.0009	-0.0273	-0.0054
	[0.7488]	[0.5681]	[0.6954]	[0.6409]	[0.79]	[0.9279]	[0.3712]	[0.8211]		

Levels of significance are ***:0.01, **:0.05, *:0.1.

Table 4.15

Predictive regressions for value premium

The table reports the results of fitting models in equations 10 and 11 with "Factor" terms set to HML premium. We tested the models over one, three, six and twelve months forecasting horizons. The first-row reports lagged explanatory variables of the model, with SENT is either ISENT when testing model 10 or CMSI when testing model 11. ISENT is a proxy for investor sentiment and calculated using principal component analysis (PCA) of three measures of investor sentiment; the number of initial public offerings, closed-end fund discounts and FTSE100 volatility index. CMSI is a proxy for managerial sentiment. RMRF is the market risk premium, SMB is the size risk premium, HML is the value risk premium and MOM reflects the momentum effect. T-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT and GDP are percentage change in industrial production level and the GDP growth rate, respectively. Data covers the period from January 2000 to September 2014 for the UK market. The table reports coefficients' estimates and [p-values] for each model. Incremental R^2 is the difference between the adjusted R^2 of the model and a basic model that does not include sentiment indices.

	(Intercept)	HML_{t-i}	$SENT_{t-i}$	$T-bill_{t-i}$	$T-spread_{t-i}$	$UNEMP_{t-i}$	IPT_{t-i}	GDP_{t-i}	$Adj-R^2$	$Inc-R^2$
Panel A: one-month										
$CMSI_{t-1}$	-0.1271	0.1297	0.0003	0.0106	0.0059	0.0183	-0.0016	0.0063	0.1219	-0.0013
	[0.0397*]	[0.0245*]	[0.468]	[0.0007***]	[0.1759]	[0.0035**]	[0.4813]	[0.159]		
$ISENT_{t-1}$	-0.0834	0.1311	-0.0010	0.0094	0.0038	0.0150	-0.0016	0.0091	0.0002	-0.1230
	[0.0054**]	[0.0106*]	[0.6470]	[0.0057**]	[0.4048]	[0.006**]	[0.485]	[0.0163*]		
Panel B: three-month										
$CMSI_{t-3}$	-0.1154	-0.0706	0.0003	0.0102	0.0064	0.0163	0.0001	0.0039	0.0480	-0.0023
	[0.1223]	[0.4627]	[0.5318]	[0.0174*]	[0.2422]	[0.0692.]	[0.9699]	[0.4663]		
$ISENT_{t-3}$	-0.0731	-0.0712	-0.0020	0.0087	0.0035	0.0130	0.0002	0.0072	0.0494	-0.0009
	[0.1041]	[0.4538]	[0.4288]	[0.0713.]	[0.5223]	[0.1266]	[0.9535]	[0.0536.]		
Panel C: six-month										
$CMSI_{t-6}$	-0.0447	0.1700	-0.0004	0.0095	0.0031	0.0139	-0.0019	0.0028	0.0009	-0.0997
	[0.4100]	[0.0094**]	[0.3667]	[0.0211*]	[0.4748]	[0.0718.]	[0.3668]	[0.5331]		
$ISENT_{t-6}$	-0.0925	0.1693	0.0010	0.0104	0.0053	0.0168	-0.0019	-0.0004	0.0013	-0.0993
	[0.0244*]	[0.0072**]	[0.7045]	[0.0138*]	[0.3155]	[0.0261*]	[0.3567]	[0.9337]		
Panel D: twelve-month										
$CMSI_{t-12}$	0.0156	0.0973	-0.0008	0.0073	-0.0025	0.0111	0.0031	0.0014	0.0901	0.0279
	[0.7273]	[0.0083**]	[0.0338*]	[0.0113*]	[0.4508]	[0.0433*]	[0.1726]	[0.6915]		
$ISENT_{t-12}$	-0.0590	0.0874	-0.0045	0.0057	-0.0035	0.0135	0.0034	-0.0005	0.0036	-0.0586
	[0.0308*]	[0.0301*]	[0.0022**]	[0.0544.]	[0.3481]	[0.0133*]	[0.1381]	[0.8818]		

Levels of significance are ***:0.01, **:0.05, *:0.1.

Table 4.16

Predictive regressions for momentum premium

The table reports the results of fitting models in equations 10 and 11 with “Factor” terms set to MOM premium. We tested the models over one, three, six and twelve months forecasting horizons. The first-row reports lagged explanatory variables of the model, with SENT is either ISENT when testing model 10 or CMSI when testing model 11. ISENT is a proxy for investor sentiment and calculated using principal component analysis (PCA) of three measures of investor sentiment; the number of initial public offerings, closed-end fund discounts and FTSE100 volatility index. CMSI is a proxy for managerial sentiment. RMRF is the market risk premium, SMB is the size risk premium, HML is the value risk premium and MOM reflects the momentum effect. T-spread is the difference in the yields between 10-Year and 3-Month Treasury bill (T-bill). IPT and GDP are percentage change in industrial production level and the GDP growth rate, respectively. Data covers the period from January 2000 to September 2014 for the UK market. The table reports coefficients' estimates and [p-values] for each model. Incremental $R^2$is the difference between the adjusted R^2 of the model and a basic model that does not include sentiment indices.

	(Intercept)	MOM_{t-i}	$SENT_{t-i}$	$T-bill_{t-i}$	$T-spread_{t-i}$	$UNEMP_{t-i}$	IPT_{t-i}	GDP_{t-i}	$Adj-R^2$	$Inc-R^2$
Panel A: one-month										
$CMSI_{t-1}$	-0.0453	0.2838	0.0008	-0.0047	-0.0029	-0.0029	-0.0004	-0.0016	0.0871	0.0053
	[0.6648]	[0.0000***]	[0.2426]	[0.3447]	[0.6163]	[0.7873]	[0.8969]	[0.7956]		
$ISENT_{t-1}$	0.0482	0.2895	0.0031	-0.0045	-0.0033	-0.0078	-0.0005	0.0019	0.0799	-0.0018
	[0.3378]	[0.0000***]	[0.4647]	[0.3947]	[0.5905]	[0.3998]	[0.854]	[0.7826]		
Panel B: three-month										
$CMSI_{t-3}$	-0.0988	-0.0894	0.0007	0.0000	-0.0062	0.0124	-0.0008	0.0092	0.0300	0.0033
	[0.3724]	[0.1892]	[0.2847]	[0.9981]	[0.3853]	[0.3862]	[0.8500]	[0.4362]		
$ISENT_{t-3}$	-0.0310	-0.0919	0.0058	0.0018	-0.0039	0.0101	-0.0011	0.0100	0.0348	0.0080
	[0.6671]	[0.1915]	[0.2763]	[0.8108]	[0.655]	[0.4621]	[0.7990]	[0.3733]		
Panel C: six-month										
$CMSI_{t-6}$	-0.0354	0.1053	-0.0001	0.0014	-0.0072	0.0147	0.0012	0.0171	0.0452	-0.0056
	[0.6828]	[0.1866]	[0.7776]	[0.8069]	[0.1447]	[0.2537]	[0.7542]	[0.0562]		
$ISENT_{t-6}$	-0.0557	0.0981	0.0016	0.0023	-0.0054	0.0162	0.0012	0.0151	0.0461	-0.0047
	[0.3166]	[0.2086]	[0.6384]	[0.7006]	[0.3387]	[0.1633]	[0.7611]	[0.1534]		
Panel D: twelve-month										
$CMSI_{t-12}$	-0.2012	0.0917	-0.0001	0.0186	0.0021	0.0444	-0.0041	0.0046	0.0861	-0.0057
	[0.0092**]	[0.2725]	[0.876]	[0.0015**]	[0.7678]	[0.0001***]	[0.1719]	[0.4839]		
$ISENT_{t-12}$	-0.2137	0.0833	0.0023	0.0193	0.0044	0.0451	-0.0041	0.0025	0.0884	-0.0034
	[0.0013**]	[0.3523]	[0.6251]	[0.0046**]	[0.6363]	[0.0001***]	[0.1618]	[0.6327]		

Levels of significance are ***:0.01, **:0.05, *:0.1.

12-month period. The negative relationship between CMSI and ISENT and HML is consistent with Lemmon & Portniaguina (2006) and Baker & Wurgler (2006) in which subsequent returns on value stocks are lower following periods of high levels of sentiment and higher following periods of low levels of sentiment. However, we found no evidence that momentum risk premiums respond to changes in either investor or managerial sentiment indices as shown by Table 4.16.

4.6. Conclusion

We examine the traditional CAPM, Fama & French (1993) three factor, and Carhart (1997) four factor models and contrast their findings against sentiment-augmented asset pricing models. Our tests focus on extending traditional asset pricing models by including investor and managerial sentiment indices. We test our models using four constructions of equally- and value-weighted return portfolios formed on size, value, standard deviation and momentum premiums. Our finding shows that managerial sentiment has strong power over investor sentiment in explaining returns of test portfolios, specifically value-weighted portfolios. In most of cases (75% of test portfolios), managerial sentiment-augmented models fail to reject the null hypothesis that model intercept terms are jointly equal to zero indicating their power in explaining stock market returns. These findings suggest that managerial sentiment index is a reliable measure of market sentiment and should be considered in behavioural-based asset pricing models.

In addition to testing alternative specifications of asset pricing models, we examined the impact of investor and managerial sentiment on size, value and momentum premiums over different forecasting horizons. We found that managerial sentiment strongly predicts size premiums over short (1 to 3 month) forecasting horizons when compared to investor sentiment. Furthermore, we found that value premiums react to changes in managerial and investor sentiment over a horizon of 12 months. On contrary, we fail to find evidence on the relationship between sentiment indices and momentum premium. Our results provide important new evidence on specification of asset pricing models and will be useful to academics and practitioners in a variety of contexts from understanding pricing of assets to costs of capital and event studies. Moreover, the findings have implications for regulators and policy makers concerned with the pricing of financial assets and regulating stock markets.

Chapter 5

Conclusion

5.1. Introduction

This chapter provides a summary of the empirical findings related to the thesis. It presents the implications and limitations of the results and discusses potential areas of future research.

5.2. Summary of the main findings

In this thesis, we provided evidence for the role of managerial sentiment in the stock market. Studies on behavioural finance implicitly assume that economic agents hold the same level of sentiment across different industries. In our study, we relaxed such an assumption and provided evidence that the sentiment-returns relationship is sector dependent. In essence, we argued that using sentiment measures at the sectoral level improves our understanding of the sentiment-returns relationship. We show that the power with which sector-specific sentiment forecasts stock returns primarily depends on the characteristics of the sector; for instance, expectations about productions and order levels forecast returns in the manufacturing and retail trade sectors. On the other hand, employment expectations exhibit an important factor in predicting construction sector returns.

In addition, the results provided interesting insights into the impact of financial crises on the sentiment-return relationship. We found that sector returns become more sensitive to sentiment after relevant crises. Sentiment associated with the manufacturing sector significantly affected sector returns post rather than predot com mania. Similar results hold for the construction sector and the sub-prime crisis. Overall, these results support our expectation that the strength and significance of the relationship between sentiment and stock returns varies between sectors.

Furthermore, we contributed to the literature by constructing a powerful predictor of stock returns, which we called the Core Managerial Sentiment Index (CMSI). In addition to forecasting a time series of stock returns, the CMSI exhibits a notable ability to explain the cross-sectional variation in stock returns relative to indicators of investor sentiment. It significantly improves the performance of traditional asset pricing models such as CAPM, Fama & French (1993) three factor model and Carhart (1997) four factor model. Moreover, we show that CMSI explains some price anomalies, such as size and value effects.

In this study, we argued that managerial sentiment drives change in investor sentiment. The findings suggest that managerial sentiment positively forecasts investor sentiment over shorter time periods. Moreover, co-integration tests indicated that managerial and investor sentiments have a longer relationship. In particular, we find that investor sentiment converges on the long-run equilibrium relationship when managers possess positive rather than negative sentiments. Furthermore, we provide evidence that managers' overconfidence leads to negative investor sentiment in subsequent periods.

5.3. Implications of the study

The findings of our study have implications for academic scholars, practitioners, fund managers, policy-makers and regulators. They provide academics who are concerned with empirical asset pricing with new insights into how managerial sentiment impacts the performance of the long-term investigated models. Individual investors are subject to asymmetric information problems when valuing the companies in which they invest. This reflects a risk factor that investors price when valuing financial assets. The power of managerial sentiment in explaining the cross-sectional variation of stock returns may reflect how investors perceive managers' signals to the market.

For practitioners, our findings suggest that managerial sentiment and its impact on sector returns provide new opportunities to enhance trading as well as asset allocation strategies. Our results indicates that managers are over-confident with regards to the future outcomes of their businesses. Their over-confidence impacts investor sentiment which, in turn, has an influence on stock prices. The finding could translate into a trading strategy in which investors short sell assets in periods with high managerial sentiment and buy them when managers disclose the financial results of their firms. In addition, fund managers may consider sectors that are more or less prone to sentiment in their investment strategies to meet investors risk preferences.

Further, the evidence on sentiment transmission from managers to investors can provide stock market practitioners with insights into when and why managers dismantle information on their businesses. Such insights will partially assist in resolving the issue of information asymmetry and will forecast the impact of managerial actions on stock returns. Regulators might also consider how their policies might be received by managers in different sectors with respect to capital and investment allocation. In addition, our results on sentiment-augmented asset pricing models may be of interest to regulators who are concerned with the estimation of businesses' cost of capital when pricing public services.

5.4. Limitations of the study

The findings and implications of this thesis should be considered in the context of the following limitations.

For the first empirical chapter, we use a shorter data period (17 years) for the services sector relative to other sectors of the UK market. Data on manufacturing, construction and retail trade sectors covers 30 years from January 1985 to December 2014. This may affect the comparability of parameter estimates, which was the main interest of the study.

For the second empirical chapter, limitation lies in the use of Principal Component Analysis (PCA) to constrict the Investor Sentiment Index (ISENT). The method mainly captures the linear correlation between its input variables, which may affect our results for two reasons; firstly, the common component of our measures of investor sentiment may reflect other macro-economic factors that have not been tested in our study. Secondly, there might be a non-linear relationship between our measures of investor sentiment; therefore, PCA might not be enough to capture the variation of the measures under investigation.

Finally, for the third empirical chapter, the correlation coefficient between ISENT and CMSI is high. The inclusion of both variables in a single model may have an impact on the results.

5.5. Directions for future research

The insights of this study provide several areas to investigate in future research. In this study, using disaggregated managerial sentiment provided a better understanding of the relationship between managerial sentiment and stock returns. Relaxing the assumption that investors hold the same level of sentiment toward different sectors may provide more interesting insights, especially when disaggregated data is available on some measures of investor sentiment, such as IPOs and turnover.

Furthermore, results for the second empirical chapter could be extended by investigating the transmission of sentiment from investors to managers. An initial investigation of this direction of the relationship, although not reported, shows significant results. Examining this further would shed some light on how the sentiment of managers is connected to what investors believe about their businesses. In addition, we suggest investigating how managerial and investor sentiments are transmitted around financial crises. Insights from this investigation could enhance the prediction of pricing bubbles and other financial crises. Moreover, we suggest expanding the study to examine other European markets, in particular when data on managerial sentiment is available by the European Commission (EC).

Finally, future research could focus on constructing a market sentiment index that takes the sentiment of different types of economic agents into consideration. In other words, a composite measure that includes the sentiments of consumers, managers and investors may provide a powerful predictor of the future state of the economy.

Bibliography

Abraham, A., Elan, D., & Marcus, A. J. (1993). Does sentiment explain closed-end fund discounts? Evidence from bond funds. *Financial Review*, 28(4), 607–616.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Investor Sentiment and Beta Pricing. *Working Paper*.

Baca, S. P., Garbe, B. L., & Weiss, R. a. (2000). The Rise of Sector Effects in Major Equity Markets. *Financial Analysts Journal*, 56(5), 34–40.

Baker, M., Stein, J. C., & Wurgler, J. (2003). When does the market matter? stock prices and the investment of equity-dependent firms. *The Quarterly Journal of Economics*, 118(3), 969–1005.

Baker, M. & Wurgler, J. (2000). The Equity Share in New Issues and Aggregate Stock Returns. *Journal of Finance*, 55(5), 2219–2257.

Baker, M. & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 61(4), 1645–1680.

Baker, M. & Wurgler, J. (2007). Investor sentiment in the stock market. *The Journal of Economic Perspectives*, 21(2), 129–151.

Baker, M. & Wurgler, J. (2013). *Behavioral Corporate Finance: An Updated Survey*, volume 2A-2B. Elsevier Inc.

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, 104(2), 272–287.

Balke, N. S. & Fomby, T. B. (1997). Threshold cointegration. *International Economic Review*, 38(3), 627–645.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18.

Bathia, D. & Bredin, D. (2013). An examination of investor sentiment effect on g7 stock market returns. *The European Journal of Finance*, 19(9), 909–937.

Bathia, D., Bredin, D., & Nitzsche, D. (2016). International sentiment spillovers in equity returns. *International Journal of Finance & Economics*.

Beattie, J. (1783). *Dissertations moral and critical*, volume 1. Mess. Exshaw, Walker, Beatty, White, Byrne, Cash, and M'Kenzie.

Beaumont, R., van Daele, M., Frijns, B., Lehnert, T., & Muller, A. (2008). Investor sentiment, mutual fund flows and its impact on returns and volatility. *Managerial Finance*, 34(11), 772–785.

Ben-David, I., Graham, J. R., & Harvey, C. R. (2013). Managerial miscalibration. *SSRN Electronic Journal*.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics*, 104(2), 363–382.

Berger, D. & Turtle, H. J. (2015). Sentiment bubbles. *Journal of Financial Markets*, 23, 59–74.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance*, 43(2), 507.

Bochkay, K. & Dimitrov, V. (2014). Qualitative management disclosures and market sentiment. *SSRN Electronic Journal*.

Bodurtha, J. N., Kim, D.-S., & Lee, C. M. (1995). Closed-end country funds and u.s. market sentiment. *Review of Financial Studies*, 8(3), 879–918.

Bondt, G. J. D. (1998). *De Economist*, 146(2), 271–301.

Bram, J. & Ludvigson, S. C. (1998). Does consumer confidence forecast household expenditure? a sentiment index horse race. *Economic Policy Review*, 4(2), 59–78.

Brown, G. & Cliff, M. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11(1), 1–27.

Brown, G. & Cliff, M. (2005). Investor Sentiment and Asset Valuation. *The Journal of Business*, 78(2), 405–440.

Brown, N. C., Christensen, T. E., & Elliott, W. B. (2012). The timing of quarterly 'pro forma' earnings announcements. *Journal of Business Finance & Accounting*, 39(3-4), 315–359.

Brown, S., Goetzmann, W., Hiraki, T., Shirishi, N., & Watanabe, M. (2003). Investor sentiment in Japanese and U.S. daily mutual fund flows.

Canbaş, S. & Kandır, S. Y. (2009). Investor Sentiment and Stock Returns: Evidence from Turkey. *Emerging Markets Finance and Trade*, 45(4), 36–52.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57.

Carroll, C. D., Fuhrer, J. C., & Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? if so, why? *The American Economic Review*, 84(5), 1397–1408.

Cavaglia, S., Brightman, C., & Aked, M. (2000). The increasing Importance of Industry Factors. *Financial Analysts Journal*, 56(5), 41–54.

Chan, K. (1985). An exploratory investigation of the firm size effect. *Journal of Financial Economics*, 14(3), 451–471.

Chan, K. S. (1993). Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *The Annals of Statistics*, 21(1), 520–533.

Chang, Y. Y., Faff, R., & Hwang, C.-Y. (2007). Does Investor Sentiment Impact Global Equity Markets ? In *EFMA 2009 Annual Meeting*: European Financial Management Association.

Charoenrook, A. (2005). Does sentiment matter? *Vanderbilt University Working Paper*.

Chen, J., Bennett, A., & Zheng, T. (2006). Sector Effects in Developed vs. Emerging Markets. *Financial Analysts Journal*, 62(6), 40–51.

Chen, J. & Sherif, M. (2016). Illiquidity premium and expected stock returns in the UK: A new approach. *Physica A: Statistical Mechanics and its Applications*, 458, 52–66.

Chen, J.-H., Jiang, C. X., Kim, J.-C., & McInish, T. H. (2003). Bid-ask spreads, information asymmetry, and abnormal investor sentiment: Evidence from closed-end funds. *Review of Quantitative Finance and Accounting*, 21(4), 303–321.

Chou, P.-H., Ho, P.-H., & Ko, K.-C. (2012). Do industries matter in explaining stock returns and asset-pricing anomalies? *Journal of Banking & Finance*, 36(2), 355–370.

Chung, S.-L., Hung, C.-H., & Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, 19(2), 217–240.

Cochrane, J. (2000). *Asset Pricing*. Princeton University Press.

Cook, D., Jarrell, S., & Kieschnick, R. (2003). Investor sentiment and ipo cycles. *Unpublished Working Paper, University of Mississippi*.

Cooper, M. J., Dimitrov, O., & Rau, P. R. (2001). A Rose.com by Any Other Name. *The Journal of Finance*, 56(6), 2371–2388.

Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006). Investor Sentiment and Pre-IPO Markets. *The Journal of Finance*, 61(3), 1187–1216.

Crane, A. D. & Hartzell, J. C. (2010). Is there a disposition effect in corporate investment decisions? evidence from real estate investment trusts.

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS: Investor Sentiment and Asset Prices. *The Review of Financial Studies*, 28(1), 1–32.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy*, 98(4), 703–738.

Doms, M. E., Jarmin, R. S., & Klimek, S. D. (2004). Information technology investment and firm performance in US retail trade. *Economics of Innovation and New Technology*, 13(7), 595–613.

Eichengreen, B. & Mody, A. (1998). What explains changing spreads on emerging-market debt: Fundamentals or market sentiment?

Elliott, W. B. (2006). Are investors influenced by pro forma emphasis and reconciliations in earnings announcements? *The Accounting Review*, 81(1), 113–133.

Enders, W. & Granger, C. W. J. (1998). Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business & Economic Statistics*, 16(3), 304.

Enders, W. & Siklos, P. L. (2001). Cointegration and threshold adjustment. *Journal of Business & Economic Statistics*, 19(2), 166–176.

Engle, R. F. & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1), 3–56.

Fama, E. F. & French, K. R. (2016). Dissecting anomalies with a five-factor model. *Review of Financial Studies*, 29(1), 69–103.

Ferrer, E., Salaber, J., & Zalewska, A. (2016). Consumer confidence indices and stock markets' meltdowns. *The European Journal of Finance*, 22(3), 195–220.

Fisher, K. L. & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal*, 56(2), 16–23.

Fisher, K. L. & Statman, M. (2003). Consumer Confidence and Stock Returns. *The Journal of Portfolio Management*, 30(1), 115–127.

Fletcher, J. (2010). Arbitrage and the evaluation of linear factor models in UK stock returns. *Financial Review*, 45(2), 449–468.

Frazzini, A. & Lamont, O. a. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, 88(2), 299–322.

Gibbons, M. R. (1982). Multivariate tests of financial models. *Journal of Financial Economics*, 10(1), 3–27.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica*, 57(5), 1121.

Glatzeder, B. M., Goel, V., & von Muller, A. (2010). *Towards a Theory of Thinking*. Springer.

Gospodinov, N., Kan, R., & Robotti, C. (2016). On the properties of the constrained hansen–jagannathan distance. *Journal of Empirical Finance*, 36, 121–150.

Granger, C. (1988). Some recent development in a concept of causality. *Journal of Econometrics*, 39(1-2), 199–211.

Gregory, A., Tharyan, R., & Christidis, A. (2013). Constructing and testing alternative versions of the fama-french and carhart models in the UK. *Journal of Business Finance & Accounting*, 40(1-2), 172–214.

Griffin, J. & Karolyi, G. A. (1998). Another look at the role of the industrial structure of markets for international diversification strategies. *Journal of Financial Economics*, 50(3), 351–373.

Guidolin, M., Hyde, S., McMillan, D., & Ono, S. (2014). Does the macroeconomy predict UK asset returns in a nonlinear fashion? comprehensive out-of-sample evidence. *Oxford Bulletin of Economics and Statistics*, 76(4), 510–535.

Hansen, L. P. & Jagannathan, R. (1997). Assessing specification errors in stochastic discount factor models. *The Journal of Finance*, 52(2), 557.

He, J., Kan, R., Ng, L., & Zhang, C. (1996). Tests of the relations among marketwide factors, firm-specific variables, and stock returns using a conditional asset pricing model. *The Journal of Finance*, 51(5), 1891.

Herbert Simon (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99.

Herbert Simon (1979). Rational decision making in business organizations. *The American economic review*, (pp. 493–513).

Hribar, P., Melessa, S. J., Small, R. C., & Wilde, J. H. (2017). Does managerial sentiment affect accrual estimates? evidence from the banking industry. *Journal of Accounting and Economics*, 63(1), 26–50.

Hribar, P. & Yang, H. (2015). CEO overconfidence and management forecasting. *Contemporary Accounting Research*, 33(1), 204–227.

Hwang, B.-H. (2011). Country-specific sentiment and security prices73. *Journal of Financial Economics*, 100(2), 382–401.

Hyde, S. & Sherif, M. (2010). Consumption asset pricing and the term structure. *The Quarterly Review of Economics and Finance*, 50(1), 99–109.

Jansen, W. & Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economics Letters*, 79(1), 89–98.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65.

Jiang, F., Lee, J. A., Martin, X., & Zhou, G. (2015). Manager sentiment and stock returns.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, 59(6), 1551.

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263.

Kan, R. & Robotti, C. (2009). Model comparison using the hansen-jagannathan distance. *Review of Financial Studies*, 22(9), 3449–3490.

Kaniel, R. O. N., Saar, G., & Titman, S. (2008). Individual Investor Trading and Stock Returns. *Journal of Finance*, 63(1), 273–310.

Kenneth Arrow (1986). Rationality of self and others in an economic system. *The Journal of Business*, 59(4), S385–S399.

Kothari, S. & Shanken, J. (1997). Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial Economics*, 44(2), 169–203.

Kumar, A. & Lee, C. M. C. (2006). Retail Investor Sentiment and Return Comovements. *The Journal of Finance*, 61(5), 2451–2486.

Lahiri, K. & Zhao, Y. (2013). Determinants of Consumer Sentiment: Evidence from Household Survey Data. *Discussion Papers from University at Albany, SUNY, Department of Economics.*, (pp. 13–12).

Laopodis, N. T. (2016). Industry returns, market returns and economic fundamentals: Evidence for the united states. *Economic Modelling*, 53, 89–106.

Lee, C. M. C., Shleifer, A., & Thaler, R. H. (1991). Investor Sentiment and the Closed-End Fund Puzzle. *The Journal of Finance*, 46(1), 75–109.

Lemmon, M. & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, 19(4), 1499–1529.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, 20(4), 587.

Louis, H. & Robinson, D. (2005). Do managers credibly use accruals to signal private information? evidence from the pricing of discretionary accruals around stock splits. *Journal of Accounting and Economics*, 39(2), 361–380.

Lucas, R. E. (1978). Asset prices in an exchange economy. *Econometrica*, 46(6), 1429.

Maasoumi, E. & Racine, J. (2002). Entropy and predictability of stock market returns. *Journal of Econometrics*, 107(1), 291–312.

Malmendier, U. & Tate, G. (2005). CEO overconfidence and corporate investment. *The Journal of Finance*, 60(6), 2661–2700.

Malmendier, U. & Tate, G. (2008). Who makes acquisitions? {CEO} overconfidence and the market's reaction. *Journal of Financial Economics*, 89(1), 20 – 43.

Marcelo, J. L. M., Quirós, J. L. M., & Martins, J. L. (2013). The role of country and industry factors during volatile times. *Journal of International Financial Markets, Institutions and Money*, 26(1), 273–290.

Mclaughlin, C. P. & Coffey, S. (1990). Measuring Productivity in Services. *International Journal of Service Industry Management*, 1(1), 46:64.

McMillan, D. G. (2001). Nonlinear predictability of stock market returns: Evidence from nonparametric and threshold models. *International Review of Economics & Finance*, 10(4), 353–368.

Meulbroek, L. K. (1992). An empirical analysis of illegal insider trading. *The Journal of Finance*, 47(5), 1661.

Michou, M., Mouselli, S., & Stark, a. (2007). Estimating the Fama and French Factors in the UK: an Empirical Review. *Manchester University Business School, Workign Paper no. 505*, (February).

Neal, R. & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? *The Journal of Financial and Quantitative Analysis*, 33(4), 523.

Nejad, M. & Huerta, D. (2014). Investor Sentiment, Recessions and Financial Industry Returns. In *The 2014 SWFA conference* (pp. 1–49).: Southwestern Finance Association.

Nichol, E. & Dowling, M. (2014). Profitability and investment factors for UK asset pricing models. *Economics Letters*, 125(3), 364–366.

Nikkinen, J. & Vähämaa, S. (2010). Terrorism and stock market sentiment. *Financial Review*, 45(2), 263–275.

Noronha, G. M. & Rubin, B. L. (1995). Closed-end bond fund discounts: Agency costs, investor sentiment and portfolio content. *Journal of Economics and Finance*, 19(2), 29–44.

Otoo, M. W. (1999). Consumer Sentiment and the Stock Market. *Working Paper*.

Phillips, P. C. B. & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica*, 58(1), 165.

Pikulina, E., Renneboog, L., & Tobler, P. N. (2017). Overconfidence and investment: An experimental approach. *Journal of Corporate Finance*.

Qiu, L. & Welch, I. (2006). Investor sentiment measures. *NBER Working Paper Series*.

Reinganum, M. R. (1981). The arbitrage pricing theory: Some empirical results. *The Journal of Finance*, 36(2), 313.

Salhin, A., Sherif, M., & Jones, E. (2016). Managerial sentiment, consumer confidence and sector returns. *International Review of Financial Analysis*, 47, 24–38.

Sanders, D. R., Irwin, S. H., & Leuthold, R. M. (1997). Noise Traders, Market Sentiment, and Futures Price Behavior. *Working Paper*.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, 16(3), 394–408.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425.

Shefrin, H. (2001). Behavioral Corporate Finance. *Journal of Applied Corporate Finance*, 14(3), 113–126.

Shiller, R. J. (1981). Alternative tests of rational expectations models. *Journal of Econometrics*, 16(1), 71–87.

Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *Journal of Psychology and Financial Markets*, 1(1), 49–60.

Shiller, R. J. (2015). *Irrational exuberance*. Princeton university press.

Shleifer, A. & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1), 35–55.

Sichel, D. E. (1993). Business Cycle Asymmetry: A Deeper Look. *Economic Inquiry*, 31(2), 224–236.

Soriano, P. & Climent, F. (2006). Region vs. industry effects and volatility transmission. *Financial Analysts Journal*, 62(6), 52–64.

Statman, M. & Solt, M. E. (1988). How useful is the Sentiment Index? *Financial Analysts Journal*, 44(5), 45–55.

Subramanyam, K. (1996). The pricing of discretionary accruals. *Journal of accounting and economics*, 22(1), 249–281.

Swaminathan, B. (1996). Time-varying expected small firm returns and closed-end fund discounts. *Review of Financial Studies*, 9(3), 845–887.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, 62(3), 1139–1168.

Throop, A. W. (1992). Consumer sentiment: Its causes and effects. *Economic Review-Federal Reserve Bank of San Francisco*, 1(1), 35.

Treynor, J. L. (1961). Toward a theory of market value of risky assets. *Unpublished manuscript*, 6.

Wang, C. (2003). Investor sentiment, market timing, and futures returns. *Applied Financial Economics*, 13(12), 891–898.

Wang, Y.-H., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. *International Journal of Forecasting*, 22(1), 109–123.

Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management*, 26(3), 12–17.

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? evidence from panel data. *Financial Review*, 46(4), 723–747.